THREE ESSAYS ON CREDIT SUPPLY

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Abstract

This thesis consists of three independent essays on credit supply, each addressing different components, including the different impact of credit supply shocks financed through different supply channels, how different credit constraints impact debt structure and productivity, and how it affects their individual and collective exposure over time.

Chapter 1: Its conceptual appeal has made the Conditional Value at Risk (CoVaR) one of the most influential systemic risk indicators. Despite its popularity, an outstanding methodological challenge may hamper the CoVaRs' accuracy in measuring the time-series dimension of systemic risk. The dynamics of the CoVaR are entirely due to the behaviour of the state variables and therefore without their inclusion, the CoVaR would be constant over time. The key contribution of this chapter is to relax the assumption of time-invariant tail dependence between the financial system and each institution's losses, by allowing the estimated parameters of the model to change over time, in addition to changing over quantiles and different financial institutions. We find that the dynamic component that we introduce does not affect the estimations for the risk of individual financial institutions, but it largely affects estimations of systemic risk which exhibits more procyclicality than the one implied by the standard CoVaR. As expected, larger financial institutions have a higher effect on systemic risk, although they are also shown to be individually more robust. When adding balance sheet data, it introduces additional volatility into our model relative to the standard one. In terms of forecasting, the results depend on the horizon used or the variables included. There is no clear outperformance between either model when we add the balance sheet data, or in the short term (less than 12 weeks). However, our model outperforms the standard one for medium (between 15 and 25 weeks) to long term horizons (between 30 and 40 weeks).

Chapter 2: We seek to evaluate the impact of the different segments within the lending sector to the private non-financial sector can have on subsequent GDP growth. We isolate the bank lending channel as one of the main components, and group the remaining ones into a second segment which we classify as market based finance (MBF). We also include the 2 different segments of the borrowing sector, household debt and non-financial firm debt, to compare with the results obtained by the standard model. We debate the main source of these effects, and focus on either credit demand or credit supply shocks, in addition to other alternatives. We find that a rise in bank credit and/or household debt to GDP ratio lowers subsequent GDP growth. The predictive power is large in magnitude and robust across time and space. The bank credit booms and household debt booms are connected to lower interest rate spread environments, as well as periods with better financial conditions. And although the overall impact on subsequent GDP growth is negative, we found contrasting evidence when using the Financial Conditions Index (FCI) as an instrument. This would point to the potential different effects that bank credit and household debt could have on future economic growth (good booms vs bad booms), depending on the underlying cause of the boom. The results and the evidence that we found are more consistent with models where the fundamental source of the changes in household debt or bank credit lie in changes in the credit supply (credit supply shocks), rather than credit demand or other possibilities. This would likely be connected to incorrect expectations formation by lenders and investors (what many authors classify as "credit market sentiment" in the literature), which is an important element in explaining shifts in credit supply. Although credit demand shocks could play an important role in prolonging or amplifying the effects of the booms, it is unlikely that they are the source, as it would lead to results that conflict with empirical evidence. Finally, we find some differences in terms of statistical significance and magnitude in the different scenarios, where the bank credit shows more robustness to different specifications than the household debt. This would imply that there is a significance of the bank credit that goes well beyond the household debt. It would also mean that the main component that generates the boom bust cycle in GDP would be the bank credit, independent of its destination, rather than household debt, independent of its financing.

Chapter 3: We construct a dataset at the firm-year level by merging the syndicated loan data, provided by Refinitiv LPC DealScan ("DealScan"), with the firm level data, provided by Center for Research in Security Prices (CRSP)/Compustat Merged Database ("CCM"). We conduct an analysis on firms subjected to different covenants, and find that firms with earnings-based constraints have lower levels of TFP (Total Factor Productivity), and short-term debt, when compared to firms with asset-based constraints. The data also shows that this is connected to an additional negative impact that short-term debt has on the productivity for the firms with earnings-based constraints, which does not verify in the firms with asset-based constraints. Both these characteristics are robust to the use of 3 different TFP estimation methods, different subsamples, and additional controls, including age and size of the firm. Thus, we consider a quantitative dynamic stochastic partial equilibrium model, with three main types of firms, distinguished by their constraints, which explores the impact of short-term and long-term borrowing on firm's balance sheets, on the different variables. We construct replications for this theoretical model, and assess the how well it fits our actual data. Our findings show that constraints exert an impact on short-term borrowing, but not on the remaining variables. More specifically, firms that face an earnings-based constraint show lower levels of short-term borrowing, compared with firms that are either unconstrained, or asset-based constraint. The adjustment is made through lower dividend distribution, as can be seen by the lower values of the value function. They also point to the impact being larger for firms with lower productivity shocks, which is in accordance with our empirical findings. Even though that our data shows differences in some of this variables (for example, on long-term debt), these were not robust to some of the controls, including the size of the firm.

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Dedications

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Declaration

I declare that, except where explicit reference is made to the contribution of others, that this thesis is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

Even though the following is mentioned in the appropriate chapter, I would also like to confirm that we resort to the code of [Cohen et al., 2021], used for the initial matching between Dealscan and Compustat data, which is publicly available. All the data used in the different chapters is publicly available.

Chapter 1

Dynamic CoVaR: Building on the ability to capture the time series dimension of systemic risk

1.1 Introduction

The economic costs of widespread failures and losses of financial institutions during the global financial crisis of 2007-09 reinvigorated the debate on how to monitor and mitigate systemic risk. The discussion remains relevant; as policymakers and academics worry that the current predicament morphs into a financial crisis. The past decade has spawned an outpouring of articles and books on how to measure systemic risk[1]. In their influential paper, [Adrian and Brunnermeier, 2016] lay the foundations of what became one of the most popular measures of systemic risk, the Conditional Value at Risk (in short, CoVaR). The premise of the CoVaR is fairly straightforward: the risk of each financial institution in isolation does not account for the externality associated with its interconnection with the overall system. To obtain an estimate of each institution's contribution to systemic risk it is necessary to focus on the distribution of losses of the overall financial system conditional on that particular institution being in distress. This contribution is captured by the ΔCoVaR which takes a center stage in [Adrian and Brunnermeier, 2016]. It measures the change in the CoVaR as one shifts the conditioning event from a median to an extreme state, typically given by the VaR_q^i, the value-at-risk calculated for a given percentile q of the loss distribution of returns for a given institution i.

One of the most appealing features of the CoVaR is its ability of capturing both the cross-section and time series dimension of systemic risk. In order to obtain a time-varying CoVaR, [Adrian and Brunnermeier, 2016] rely on the introduction of state variables to their original specification, which reflect time variation in the conditional moments of asset returns. Such a

[1] The vast literature on the subject is nicely reviewed by [Bisias et al., 2012, Peydro et al., 2015] and [Benoit et al., 2017].

modelling choice has an important implication which motivates our paper. The dynamics of the time-varying CoVaR are entirely due to the behaviour of the state variables. Without their inclusion, the CoVaR would be constant over time. Although the time dimension of systemic risk relates to the complex and ever changing tail dependencies between institutions in the network of firms which form the financial system, the time-varying CoVaR assumes a static dependency between each institution and the financial system's loss distributions.

The key contribution of this paper is to relax the assumption of a time-invariant tail dependence between the financial system and each institution's losses. The parameters governing the relationship between state variables and tail risk are also allowed to vary with time, giving the model additional flexibility. Our starting point is an estimated quantile regression that replicates the results presented by [Adrian and Brunnermeier, 2016]. We, then, extend this baseline specification so as to accommodate time-varying parameters. Quantile regressions, as introduced by [Koenker and Bassett, 1978], seek to explain quantiles of the conditional distribution of the response variable as a function of observed covariates. They, therefore, capture non-linearities between the dependent and independent variables, since the marginal effect of a given covariate is allowed to change across quantiles. However, they are still linear in the parameters - the coefficients governing the marginal effect between each independent variable and a given quantile of the dependent variable's conditional distribution are constant. We argue that this is an undesirable feature for the estimation of the CoVaR. If changes in tail dependencies between each institution and the financial system ought to move over time, the parameters in the model governing such a relationship should accommodate that possibility.

We start by formalizing the CoVaR as a Bayesian quantile regression model in the spirit of [Yu and Moyeed, 2001]. A Bayesian environment allows us to adopt well established methods used in the literature to model parameter time-variation. Although the innovations of a quantile regression are not gaussian, they may be written as a scale mixture of normals (see [Kotz et al., 2001]), which allows the re-specification of the quantile regression such that standard methods for Bayesian inference can be applied. We extend the Gibbs Sampler proposed by [Kozumi and Kobayashi, 2011] to accommodate time-varying parameters. Our strategy consists in realizing that the quantile regression admits a state space representation. Thus, the application of the Kalman filter algorithm proposed by [Carter and Kohn, 1994] is possible.

In order to make sure that the differences between the results in the original article and our model stem from the introduction of the time-varying parameter component, and not from the different estimation method chosen, we begin by estimating the quantile regressions using both methods (the frequentist approach used in [Adrian and Brunnermeier, 2016], and the Bayesian approach that we use in our model), before incorporating the time-varying parameter component. Our estimations between the frequentist approach and the Bayesian approach are exceedingly similar. Thus, the difference between our results and those of the original article are caused by the time-varying parameter component, and not from the usage of different estimation methods.

Our results show that the estimations for the VaR are exceedingly similar between the two models, and we can infer that the dynamic component that we introduced does not affect the estimations for the risk of individual financial institutions. On the other hand, the estimations for the CoVaR are starkly different, reflecting the influence of the dynamic component on systemic risk analysis instead. In fact, the introduction of time-varying parameters leads to an increase of the volatility of the CoVaR in general, pointing to a higher procyclical component of systemic risk than in the traditional model. Procyclicality occurs because risk-taking is high when volatility is low, giving rise to a 'volatility paradox' [Brunnermeier and Sannikov, 2014]. As expected, this is likely due to the introduction of additional sources of risk: that tail dependency between the loss distributions of the financial system and of each individual institution can change over time, as well as the effect between state variables and tail risk. More specifically, with the introduction of the dynamic component into the model, we can conclude that the differences result from the changes of the impact of the state variables on the dependent variable (systemic risk) over time, or from the change of the impact of the individual risk of each institution in the systemic risk over time (or a combination of both). The first scenario would point to the exposure of the financial system to macroeconomic conditions changing overtime, while the second scenario would imply changes in the conditions within the financial sector itself. We also confirm the feeble connection between individual risk and systemic risk across institutions, but a strong link between them across time, both of them obtained in [Adrian and Brunnermeier, 2016]. As expected, larger financial institutions have a higher effect on systemic risk, although they are also shown to be individually more robust. This would imply that, as long as they are financially solid, they contribute less to systemic risk. But as they become financially unstable, their contribution to systemic risk surpasses smaller financial institutions. When adding balance sheet data, it introduces additional volatility into both series, and, generally, reflects more conservatives/negative estimates of our DCoVaR, relative to the standard CoVaR model. In terms of forecasting, the results depend on the horizon used or the variables included. There is no clear outperformance between either model when we add the balance sheet data, or in the short term (less than 12 weeks). However, our model outperforms the model of [Adrian and Brunnermeier, 2016] for medium (between 15 and 25 weeks) to long term horizons (between 30 and 40 weeks).

The structure of the paper is as follows. Section 1.2 reviews the relevant literature related to our topic. Section 1.3 describes the methodology for the estimation of the CoVaR, discusses its properties, and highlights the changes to this methodology, so as to accommodate time-varying parameters, and arrive at our DynamicCoVaR (DCoVaR). Section 1.4 presents the econometric approach and motivates the contribution of a time-varying parameter approach for the estimate of the CoVaR. Section 1.5 outlines the Data used throughout this study. Section 1.6 discusses the results obtained in our standard framework. Section 1.7 introduces balance sheet data to our estimations. Section 1.8 reflects how our standard results are affected by the additional data. Section 1.9 provides the conclusions of this paper.

1.2 Literature Review

1.2.1 VaR

Description of the measure

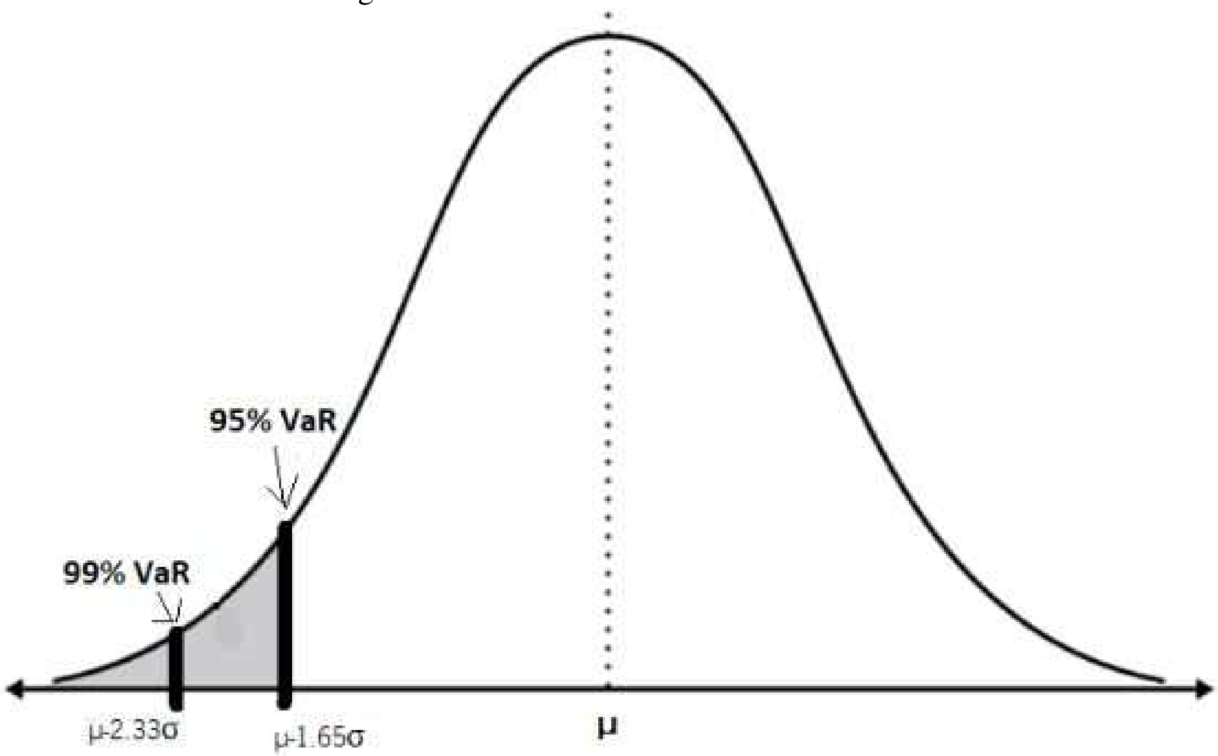
In this section, we develop on the importance and popularity of the Value at Risk (VaR) as a measure of risk exposure of financial institutions, both in terms of the academic literature, as well as in terms of the financial regulatory and supervisory authorities. We also explain the limitations of the VaR, and the relevance of the Conditional Value at Risk (CoVaR) measure proposed by [Adrian and Brunnermeier, 2016] in mitigating these shortcomings.

We begin with a general explanation of the Value at Risk. In general terms, the VaR can be seen as an estimation measure of the amount of losses for a specific investment, or a specific financial institution, associated with a particular probability. In our case, we will be more interested in the second scenario, that is, the losses for financial institutions. For example, the VaR establishes that a certain financial institution X will not have losses higher than Y, with a probability of 95%. In this example, this implies that the VaR is also reflecting that there is a probability of 5% that the financial institution X will have losses higher than Y. In other words, it means that, for an average of each 100 days, in 95 of them, the losses will be lower than Y, and in 5 of them, the losses will be higher than Y. Of course, this is not likely to verify for each of the 100 days in the sample (hence why we define in terms of the average), as the majority of significant losses will be concentrated in periods of crisis. As a result, the value Y can, then, be seen as an estimation of the boundary that distinguishes between the losses in regular periods and in periods of crisis.

One can also adjust the probability for looser or more conservative estimates. The lower the probability associated with the losses higher than Y, the more certainty we are attributing to the estimates, and the higher the value of Y has to be to reflect this certainty. This lower probability could then, be associated with the distinction between losses in regular periods, or relatively mild bubbles or downturns, and extremely severe recessions/depressions (for example, the 2008 Great Financial Crisis). Returning to our example, this would be the case where we establish that the losses will not higher than Z, with a probability of 99%. This implies that only 1% will be higher than Z, and that Z has to be higher than Y. Therefore, the values of Z and Y reflect the values of the VaR for different probabilities/quantiles in the distribution of losses. We can observe this more clearly by looking into Figure 1.1, for a normal distribution of returns with μ and standard deviation σ.

For a more specific definition of the VaR, we resort to the information in [Holton, 2014]: ' *For a given time period and probability, a value-at-risk measure purports to indicate an amount of money such that there is that probability of the portfolio not losing more than that amount of money over that time period. Stated another way, value-at-risk purports to indicate a quantile* *of the probability distribution for a portfolio's loss over a specified time period*'. In other words, the VaR is defined as the amount of potential loss from adverse market movements over a defined time period that cannot be exceeded in x% of cases.

Figure 1.1: Distribution of returns



Notes: VaR for Normal distribution. The graph illustrates the VaR for two confidence levels when returns are normally distributed. The values of μ can be read from the standard normal distribution tables

For the calculation of the VaR, we need to specify 3 elements: 1 - The period of time (or overall horizon) over which the possible loss will be calculated. In our case, we will consider the entire time period defined for the sample, until the last period in question; 2 - the quantile of the possible loss. In our case, we will focus on the 0.95 quantile scenario, but also present estimations for other quantiles; 3 - the unit measure of the losses. In our case, we will consider the unit to be in terms of the weekly/quarterly market equity loss rates.

We also need to consider the types of risk that are taken into account by the VaR. First, we need to consider the 2 possible components of risk: 1 - dimension; 2 - uncertainty. In the first component, we are concerned with the amount of (potential) losses, while in the second, we are considering the likelihood of these losses manifesting. We also need to quantify these 2 components. While the first one is straightforward, quantifying uncertainty entails higher complexity. Usually, this is done through a probability distribution, which is also the case of the VaR.

Next, we need to consider the type or potential source of risk. We will be mostly focused on financial risk, which can be broken down it 4 broad categories: market risk; liquidity risk; credit risk; and operational risk. Market risk can be defined as the risk of losing resources due to factors that affect the overall financial markets, or due to adverse movements in the volatility of market prices and can be explained either in terms of absolute risk, that is, as a measure of the volatility of total returns, for a given amount, or relative risk, that is, as a measure of the deviation of the returns compared to a benchmark index. These factors include interest rates, exchange rates, equity prices, commodity prices, and others.

Liquidity risk relates to the difficulties of sustaining significant losses which were unexpected, and can be subdivided into 2 main components: market liquidity risk, which is the loss incurred when a market participant wants to execute a trade or to liquidate a position immediately, or in a short notice, at a lower cost while not taking advantage of the best price; and funding liquidity risk, which the Basel Committee defines as the ability of a financial institution to meet the cash flow and collateral need obligations, unwind or settle their positions as they fall due. A more general definition of liquidity risk can simply be put as the inability to meet the short-term debt obligations, or the lack of enough liquid resources to meet these obligations, leading to the possibility of incurring losses, and, in some extreme cases, may even lead to defaults.

Credit risk results from the uncertainty regarding the counterparty's potential inability or unwillingness to comply with their contractual obligations. It can occur before an actual default and often does not occur in isolation. The 2 major components of credit risk are: sovereign risk, which is the risk that a government could default on its debt (sovereign debt) or other obligations; and default risk or counterparty risk, which is applied to private entities, and describes the likelihood or probability that one of those involved in a transaction might default on its contractual obligation.

As for operational risk, it arises from losses owing to inadequate internal processes, people, systems and from external events. Examples include possible malfunctions in the flow of information, legal issues or costs, and rogue trades. While the VaR will be focusing more on some of these risks (for example, market risk), it is also able to take all them into account, depending on the variables that are included in the model, as we will see later on. In regulatory terms, the VaR is used as a measure for market risk and credit risk (and, in some specific cases, even for exchange rate risk). For example, the Integrated Stress VaR is used both for credit risk and exchange rate risk.

Not only that, but we can also see, from the definition, that the VaR focuses on extreme events, or large losses, or tail risk scenarios. [Mishkin, 2009] and [Orlowski, 2012] use the term "tail risk" to define events with very low frequency (that is, very rarely happen), but with highly significant losses. [Tolikas, 2008] defines tail risk in terms of "chances" and "consequences", where the chances refer to the probability of the event (either empirical or theoretical probability distributions) and the consequences are the low returns (or large losses) in the tails of the return distribution. The focus of the VaR, or the tail risks, is on the outliers (mostly, the negative outliers) of the distribution. [Kemp, 2011] explains that this type of risk results from fat tails, more specifically, from skewness of the distribution from the left (leptokurtosis). This characteristic manifests in empirical studies when volatility of asset prices is not constant overtime, that is, during regular/normal periods, volatility is low, but highly increases in periods of crises. The exact values to establish the threshold have not been decided, where [Kemp, 2011] establishes the tail risk at 10% quantile, while [Smith, 1987] defines in terms of standard deviations, considering these extreme events to be beyond 2.6 standard deviations from the mean.

In terms of the advantages of the VaR, we can include the forward looking element of this indicator, that is, not only are we able to use this measure to infer on its accuracy, by comparing with the past market equity losses, but we also can use it to predict future market losses. A good example in our case is the analysis we make on the potential market equity losses from the COVID-19 pandemic, using data only from the initial periods of the pandemic, which we will get to in more detail later on. This measure can also be considered as easily understandable for non-specialists, and the estimation of risk is reasonably consistent. One final advantage is that it can be used to hold financial institutions accountable for potential limit violations (as it has been used by financial regulators and supervisors, as we will describe below). In terms of the disadvantages, the main issue could be in terms of potential manipulation of this measure. Even though it is relatively easily understandable, the complexity for the actual calculations can render them rather vulnerable. And this complexity in calculation would constitute the other disadvantage, connected with the computationally expensive aspect, as well as difficulties for implementation.

Application in regulatory law

We follow with an historical analysis of the VaR, as described by [Holton, 2014]. The author explains that, even though the specific terminology 'VaR (Value-at-Risk)' only started being used in the 1990s, the original measures (more specifically, with capital requirements) started being applied in the 1920s. This was first applied to the firms listed in the New York Stock Exchange (NYSE), where capital requirements would be of 10% of property assets and consumer receivables. Shortly after (in 1929), this initial rule was extended into several subcategories: 1 - 5% were established for customer debits; 2 - the 10% were applied only to property in government or municipal bonds; 3 - 30% were applied to property holdings in other liquid assets; 4 - 100 % on property holdings in all other assets. In 1975, these requirements were generalized to all US broker-dealers trading securities (excluding a few exceptions, which were exempt). Instead of the previous 4, there were now 12 main categories (which included public debt, corporate debt, preferred stock, among others), which were further divided into subcategories, mainly differentiated according to maturity. The Securities and Exchange Commission (SEC) instated a Uniform Net Capital Rule (UNCR), in which, for these several categories and subcategories, a system of 'haircuts' was implemented, such that the different institutions would be able to liquidate these assets in the case of significant market losses. Additional haircuts could be applied according to the concentration in specific assets, or a single asset. In 1980, the SEC re-defined these haircuts according to the statistical analysis of historical market data. The goal was to provide an estimation of the quantile of 0.95 of losses from an institution over 1 month. Notice that this is exactly a VaR type of measure. In the 1990s, several regulatory authorities started incorporating Value-at-Risk measures directly, including: 1 - the UK's Securities and Futures Authority in 1992; 2 - Europe's Capital Adequacy Directive (CAD) in 1993; and 3 - the Basel Committee's in 1996, similar to the CAD.

Based on [Holton, 2014], we define the Basel Committee on Banking Supervision as being a standing committee comprising representatives from central banks and regulatory authorities. Over time, the focus of the committee has changed, comprising of initiatives intended to establish the roles of regulators in cross-jurisdictional situations; guarantee that international banks or bank holding companies are included in the comprehensive supervision framework, and do not take advantage of more laxed regulatory restrictions; and foster uniform capital requirements so banks from different countries may compete with one another on a "level playing field". Although the Basel Committee's recommendations cannot be enforced by law, the G-10 countries have often implemented those recommendations as statutes or regulations themselves, not only to fulfil the "level playing field" component, but also to lead by example for other countries.

Financial regulatory and supervisory authorities have also incorporated the VaR into the requirements of financial institutions. Historically, given the complexity of the financial operations, and the potential differences between financial institutions, regulators have, instead of directly monitoring and supervising all activities of said institutions, opted for requiring banks to hold enough capital and resources to properly address the risk inherent to the activities that they have selected. These resources are defined as the capital requirements, which are established in the Basel Accords, a form of international agreements, and monitored by domestic and/or supranational regulatory and supervisory authorities. The VaR measure was introduced in the regulatory framework in 1996, to specify capital requirements to address market risk. In the initial formulation, institutions (which, at this time, only consisted of banks, that is, only banks were considered by these requirements) could use the relatively simple formulation established in the international Basel Accords, or they could use their own measure of the VaR, as long as the methodology was previously approved by the regulators themselves.

According to the Basel accords, *VaR is an important tool in monitoring aggregate market risk exposures and provides a common metric for comparing the risk being run by different desks and business lines. A bank's VaR model should be adequate to identify and measure risks arising from all its trading activities and should be integrated into the bank's overall internal capital assessment as well as subject to rigorous on-going validation. A VaR model estimates should be sensitive to changes in the trading book risk profile*. This initial metric was established for a quantile loss of 99%, and the period of time was defined at 10 days. The currency would be defined according to the currency of the domestic country. One of the reasons to allow financial institutions to use their own measures of the VaR, instead of the standard one, is to include additional flexibility into the measure, in order to reflect the differences inherent to their operations, which may be able to better capture its risk and benefits. For example, these measures would allow for the specification of the profits and the corresponding capital requirements of a product, or a unit within the business.

Larger financial institutions, who may pose a larger threat to financial stability, could also be required to provide additional information on market risk, potentially arising from changes in interest rates, exposure to foreign exchange, or to specific markets or commodities. After a few years, the calculations for the VaR to comply with regulatory requirements was updated to the maximum between a VaR (quantile loss of 99%, to 10 days of holding positions) of the previous day and the average daily VaR from the last 60 days, multiplied by a factor (in Basel II). With the Basel III accords, this was changed to the maximum between the last VaR in a stressed situation and the average of the stressed VaR of the last 60 days, multiplied by a factor. The choice of historical observation periods (sample period) for calculating value-at-risk were constrained to a minimum length of one year. Financial institutions had to update their data sets no less frequently than once every month and also reassess them whenever market prices are subject to material changes. This updating process must be flexible enough to allow for more frequent updates. In terms of the type of VaR model (which we will see below in more detail), there is no specific one that is prescribed by supervisory or regulatory authorities, and can include, for example, variance-covariance matrices, historical simulations, or Monte Carlo simulations.

In addition, financial institutions must also calculate a stressed value-at-risk (sVaR) measure. This is intended to replicate a value-at-risk calculation that would be generated on the financial institution's current portfolio if the relevant market factors were experiencing a period of stress. As an example, for many portfolios, a 12-month period relating to significant losses in 2007/2008 would adequately reflect a period of such stress, although other periods relevant to the current portfolio must be considered as well. The Basel accords also advise that different techniques might need to be applied to translate the model used for value-at-risk into one that delivers a stressed value-at-risk. For example, for applying absolute rather than relative volatilities to deliver an appropriate stressed value-at-risk, or using anti-thetic data[2], firms should consider modelling valuation changes that are based on the magnitude of historic price movements, applied in both directions – irrespective of the direction of the historic movement. For instance, if a time series included a notable upward spike in equity prices, the model could apply significant movements in equity prices both upwards and downwards. This might be particularly relevant

[2] In statistics, the antithetic variates method is a variance reduction technique used in Monte Carlo methods. Considering that the error in the simulated signal (using Monte Carlo methods) has a one-over square root convergence, a very large number of sample paths is required to obtain an accurate result.

if a financial institution's portfolio is the "right way" to a period of financial stress (that is, long equities in a period of stock market surge), the model used should reflect that open risk positions (in either direction) are vulnerable to stressed variables.

The legislation also defines additional stress tests (factor shocks or integrated scenarios whether historic or hypothetical) and other appropriate risk management techniques, which should include: illiquidity/gapping of prices; concentrated positions (in relation to market turnover); one-way markets; non-linear products/deep out-of-the-money positions; events and jumps-to-default; significant shifts in correlations; and other risks that may not be appropriately captured in the VaR (e.g. recovery rate uncertainty, implied correlations or skew risk). A specific component within the VaR that is also established in the Basel accords is the Economic Value at Risk (EVaR), which measures the expected maximum reduction of market value that can be incurred under normal market circumstances over a given time horizon or holding period and subject to a given confidence level. For calculation of the EVaR, the changes in the market value of the banking book and, thus, of the equity, are computed for a set of alternative yield curve scenarios. When the EVaR approach is applied to the banking book, the time horizon is normally consistent with the economic model of the banking book.

Not only that, in the Basel III accords, as well as Basel IV proposals for 2023, the VaR calculations and adaptations are taken into account for different types of risk, and applied for different types of operations. This is defined in more detail on the recent Basel Framework, by the Basel Committee on Banking Supervision (BCBS). For example, for the value-at-risk (VaR) charge for specific risk, the Basel Accords establish that financial institutions should work with their supervisors to develop an approach that would translate these charges into individual instrument risk weights that would then be allocated to the geographic location of the specific counterparties that make up the charge. VaR models can also be used for calculating potential price volatility for repo-style transactions and other similar securities financing transactions (SFTs), as well as for margin lending transactions.

In establishing the characteristics for the internal VaR models, they must adequately explain historical price variation, capture both the magnitude and changes in the composition of potential concentrations, and be robust to adverse market environments. The overall population of risk exposures represented in the data used for estimation must be closely matched to or at least comparable with those of the bank's equity exposures. The VaR can also be used to take into account the covariance and correlation in the equity portfolio of the financial institutions, within broad risk categories (for example interest rates, exchange rates, equity prices and commodity prices, including related options volatilities in each risk factor category), which must be fully documented and supported using empirical analysis, while the implicit correlation assumptions are to be evaluated by supervisors. The VaR may also be used to calculate the Exposure at Default (EAD), as well as incorporate the collateral value used to minimize the losses in extreme scenarios, and possibilities of rating migrations (especially in the case of rating decreases), as well as credit derivatives for securitization exposure, and hedge positions only when they mitigate credit valuation adjustment (CVA) risk. For options risk, the Basel accords specify that the VaR models must capture the non-linear price characteristics of options positions, and also must have a set of risk factors that captures the volatilities of the rates and prices underlying option positions, that is, the vega risk, divided by different maturities. The gamma risk (second-order sensitivities to shifts in risk, for example, in credit spreads) can also be incorporated in the VaR calculations.

The summary of the list of central information that financial institutions have to provide to supervisory and regulatory authorities for the VaR and stressed VaR models is as follows: 1 - description of activities and risks covered by the VaR models and sVaR models. Where applicable, financial institutions must also describe the main activities and risks not included in VaR/sVaR regulatory calculations (due to lack of historical data or model constraints) and treated under other model risk measures (such as specific treatments allowed in some jurisdictions); 2 - specify which entities in the group use the models or if a single model (VaR/sVaR) is used for all entities with market risk exposure; 3 - general description of the models (VaR/sVaR); 4 - discussion of the main differences, if any, between the model used for management purposes and the model used for regulatory purposes.

In addition to the previous points, for the VaR models, they must also provide: i) Data updating frequency; ii) Length of the data period that is used to calibrate the model, and, obligation to describe the weighting scheme that is used (if any); iii) How the financial institution determines the 10-day holding period. For example, does it scale up a one-day VaR by the square root of 10, or does it directly model the 10-day VaR; iv) Aggregation approach (method for aggregating the specific and general risk): does the financial institution calculate the specific charge as a standalone charge by using a different method than the one used to calculate the general risk or does the it use a single model that diversifies general and specific risk?; v) Valuation approach (full revaluation or use of approximations); vi) When simulating potential movements in risk factors, describe whether absolute or relative returns (or a mixed approach) are used (i.e. proportional change in prices or rates or absolute change in prices or rates).

As for the stressed VaR models, they must moreover lay out: i) How the 10-day holding period is determined. If the approach is the same as for the VaR models, the financial institution should confirm this; ii) The stress period chosen by the bank and the rationale for this choice; iii) Valuation approach (full revaluation or use of approximations); iv) Description of stress testing applied to the modelling parameters; v) Explanation of the approach used for backtesting/validating of the accuracy and internal consistency of data and parameters used for the internal models and modelling processes.

Interestingly enough, we can see that most of the changes and measures we described in the historical analysis started being applied after the 1980's. [Chakraborty et al., 2021] argue that the origins of tail risk are connected to the increasing influence of the financial sector on the real economy, particularly, economic policy making. This connection is argued to constitute an incentive to the origination of asset price bubbles, which burst with the subsequent dire market information. In fact, despite the analysis of the origin of rare and extreme negative events in the financial market that spillover to the rest of the economy being new, their documentation and identification are properly made in history since the Dutch Tulip crisis in 1636.

A more detailed analysis is provided in Table 1.3. Following to the 1700's, there were 2 major events identified: the South Street Sea bubble in 1720 and the crash from the end of "Seven Years War" in 1763. Next, the 1800's saw 4 major events, based on the defaults on sovereign debt across Europe and Latin America, and then the Panic of 1873 in the US, Austria and Germany. In the 1900's, we have a total of 10 major negative events, where the roots of 3 of them can be traced to a banking crisis, more specifically, the crisis in 1907 and 1929 (which originated the "Great Depression"), and the Spanish component of the "Big Five Crisis" in Spain. Finally, so far in the 2000's, 8 major negative events have been identified, with the most notorious one being the Global Financial Crisis (GFC). And the extreme events identified have only been until 2020's, so it is highly likely that the 2000's will have more extreme negative events than the 1900's.

This conclusion also seems to be shared by other authors. [Tomaskov-Devey and Lin, 2011] inform that financialization of the real economy has resulted in the replacement of labor income from active sources with financial asset prices income from passive sources, since the 1980's, as the main source of national wealth. Not only that, [Cieslak et al., 2019] expose the asymmetric behaviour of the response of unemployment to the market indices. That is, the increase in unemployment due to a decrease in equity indices is higher than the decrease in unemployment due to an increase in market indices. In the recent years, we have also witnessed a shift of borrowing, by corporations, governments and public entities, from banks to financial markets. Most of the resources of Financial Intermediaries (FI) are not obtained from granting credit and other intermediation services, as it is with traditional banks, but instead, from the trade of financial securities, securitized loans, and other products connected to financial markets. Therefore, the financialization shifts the source of risk from credit risk to market risk. Not only that, the regulatory measures are more focused on banks and other traditional financial institutions, leaving lower surveillance and oversight on financial intermediaries.

Given this shift, financial regulators and supervisors have also added unconventional monetary policy (UMP) as a tool to address these new risks. As the name indicates, these usually involve the use of tools that fall out of line with traditional measures, which include quantitative easing, forward guidance, and collateral adjustments. This is also supported by [Karwowski et al., 2017], who explains that, as financial intermediaries start to replace banks and other traditional financial institutions as the main providers of resources, there is a rise in the need to implement asymmetric or unconventional monetary policy (UMP) via financial markets, putting the stabilization of financial asset price as a secondary objective.

However, as explained by [Zhang et al., 2020] and [Wójcik and Ioannou, 2020], in their assessment of the swift asset price falls during the COVID-19 pandemic in developed countries and, in one case, more specifically focused on China, seem to attribute that effect to the use of UMP responses. This is also consistent with the findings of [Cieslak et al., 2019] and [Lian et al., 2019], which point to the unintentional side-effect of the UMP policies contributing to the speculation and destabilization in financial markets, which may cause unsustainable asset price inflation for 15 to 40 months, resulting in extreme financial and economic market events. Through this component, the effects of these negative extreme financial events can spillover and spread to the real economy, and impact agents outside the financial sector, especially households. Thus, the exposure of the financial system and the extreme losses during these crisis show that these financial intermediaries do not allocate enough capital and resources to shield themselves against a potential default in these conditions, and the primary goal of the financial regulators and supervisors, both on a national and a supra-national level, is to enhance the initial detection of these extreme events in an early stage.

This gives rise to the measurement of these extreme risks being a very central and important tool to use to achieve this objective. More recently, the Supranational consortium of financial regulators, such as the Basel Committee of Banking Supervision (BCBS), and the Bank of International Settlements (BIS), have also included the financial intermediaries in the obligation for the calculations of the VaR for the estimation of required market risk capital buffers (see [on Banking Supervision (BCBS), 2019]).

In terms of the indicators to measure extreme risk, or tail risk, being used over the years, the initial ones correspond to the traditional standard deviation of asset price returns (simple calculation of the deviations from the mean), followed by the stop loss limits during market trades (basically, introducing limitations to the amount of risk exposure). Adding to these, we have the gap analysis, which calculates the difference in the net income due to asset and liability sensitivity towards interest rates. The sensitivity metrics were added to this list, which include the "beta" for equities, "duration" and "convexity" for bonds, and "greeks" for options, and consist of the first and second order conditions of the asset prices with respect to the risk factors. Later, capital buffers such as Margin Amount and Risk Capital represent the extreme market risk in terms of capital amount. As we discussed, their goal is to be able to create additional protections in the case of extreme losses, and being able to absorb, at least, a significant portion of those losses. And although the measures serve to either diminish or absorb part or all of the losses from these tail risks, none of them is strictly preferable, with each one of them having advantages and disadvantages.

More importantly, all of the previous measures focus on the consequences of the losses, and do not explicitly address the probabilities (more specifically, the probability distribution) of those losses. This central hindrance was addressed through the use of the Value at Risk (VaR) (and other measures, including the Expected Shortfall), which are probabilistic statements of extreme losses. Comparing the two measures, the VaR is a tail quantile that represents the probability boundary for extreme market losses, while the Expected Shortfall measures the average of losses greater than the VaR. A more detailed comparative analysis of these measures is provided by [Jorion, 2010] and [Kellner and Rösch, 2016].

Estimation Methods

In this subsection, we explore the estimation procedures that are used for the VaR. There seems to be three initial fundamental estimation methodologies of the VaR, as described by [Choudhry, 2013]: 1 - analytical procedures based on Gaussian/Normal distribution; 2 - non-parametric Historical Simulation (HS); and 3 - semi- parametric Monte-Carlo Simulation (MCS). However, there are some limitations of these initial measures. For the case of the Gaussian distribution, the limitations are rather obvious, since the Normal distribution underestimates the probabilities at the tails of the distribution, and does not account for other empirical elements. Since the extreme events are captured at the tails of the distribution, this is an issue for the measure of the VaR. As an alternative, non-parametric Historical Simulation (HS) started being applied.

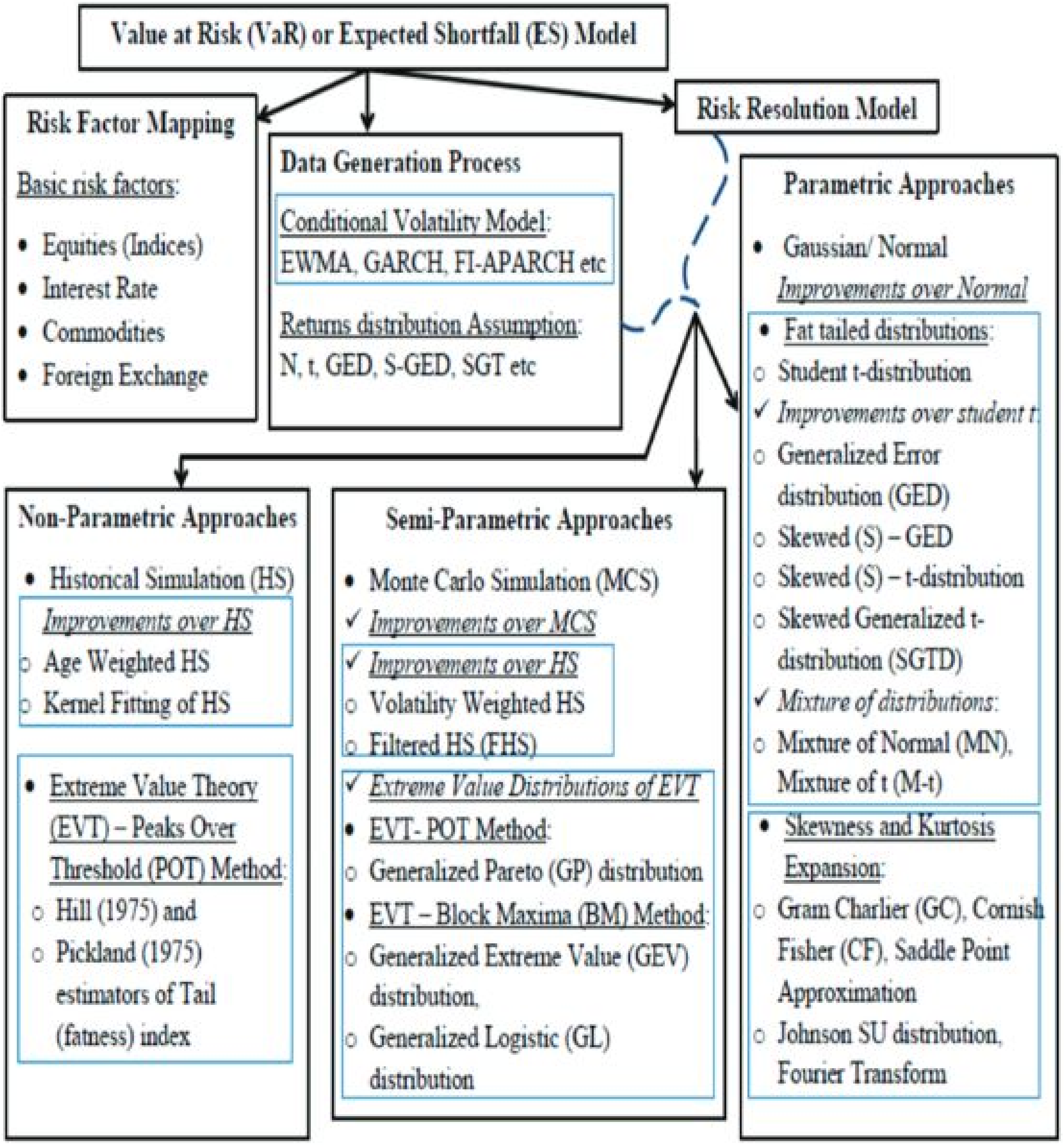
As established by [Hendricks, 1996], [Jackson et al., 1997], and [Vlaar, 2000], the Historical Simulation seems to achieve better VaR estimates than the Normal approaches. First of all, one of the most obvious reasons is by taking into account the empirical distribution, which incorporates the fat tails characteristic. But it also allows for the no taking of assumptions on the distribution, allowing additional flexibility to match the data. Not only that, it is very intuitive, easy to calculate and communicate the results, and simple to present confidence intervals for the VaR estimates. In fact, [Huang and Tseng, 2009] find that it is even marginally more accurate than the third method, the Monte Carlo Simulation, due to a higher matching of the tail probabilities. The main problem with the historical simulation is that it does not seem to be a very precise estimator. Even though the tails component seems to be a good match in comparison with the other estimators, the standard errors for the overall series are extremely high, making it a difficult match for the overall series.

Given the inaccuracies of these traditional measures, some alternatives were considered. A summary of the classification and comparison of the different methods to estimate the VaR (and the Expected Shortfall), is given in Figure 1.2, and are analyzed in more detail in [Chakraborty et al., 2021]. In terms of univariate risk metric estimation, we have 3 types of models: risk factor mapping, the data generation process, and the risk resolution model. As we can see, the risk factor mapping takes into account a list of different risk factors, which constitute potential different exposures of the market value of assets to these risks. And this is done through either partial derivatives on a pricing function (for example, the Black Scholes formula) or through regression (for example, the CAPM). In most cases for this method, the likely non-linear relationship between risk factors and the market value of assets is approximated through a linear relationship. For the data generation process, it resorts to volatility clustering effects to achieve a higher fitting of the returns distribution to the change of the returns series over time. In other words, the theoretical distribution is going to be assumed for the returns (either for the overall distribution, or simply to focus on the tails, for extreme events), conditional on the assumption of the change in the returns' process. If the volatility clustering effects are not considered, then the model is classified as "unconditional". The combination of these first 2 components, the risk mapping and the data generation process leads to the risk resolution model, which, itself, consists of 3 components: non-parametric, parametric and semi-parametric.

Starting with the parametric approaches, they can be further subdivided into 3 main strands: 1 - conditional (time-varying) volatility model, so that it properly incorporates the time-varying volatility component, including potential asymmetric characteristics (in Figure 1.2, these are included under the "Data Generation Process"); 2 - focusing on the fat tails and skewness components of the parametric distribution that explains the empirical returns distribution; 3 - incorporate higher moments of the distribution (including the skewness and kurtosis) to better match the empirical data. Within the first strand, we can further distinguish between 3 approaches: 1.1 - GARCH type models (which include [Gónzalez-Rivera et al., 2004], [Chen et al., 2012], [Sener et al., 2012], and [Abad et al., 2014]); 1.2 - stochastic volatility models (for example, as in [Lehar et al., 2002], [Fleming and Kirby, 2003], [Gónzalez-Rivera et al., 2004], [Chen et al., 2012], and [Clements et al., 2008]); 1.3 - and realized volatility models (as discussed by [Clements et al., 2008], and [Asai et al., 2012]). In terms of the analysis of the performance of these different types of parametric models within the time-varying volatility component, the empirical data points to the accuracy of forecasting of VaR estimates between "1.1 GARCH methods" and "1.2 stochastic volatility methods" being similar (as established in [Chen et al., 2012], for example), while the 1.3 realized volatility methods seem to achieve a higher performance in terms of VaR forecasting accuracy (as well as some variations of the GARCH models, as explained in [Giot and Laurent, 2003] and [Brownlees and Gallo, 2011]). However, when we compare with other main parametric approaches, in terms of accuracy of VaR estimates, it seems that the parametric distribution fitting of return distributions (our 3^{rd} measure in the description) achieves better results than the conditional volatility model (any of the measures we described in point 1, see [Abad et al., 2014], for example).

We move on to the analysis of the 2^{nd} strand within the parametric approach, which incorporates large tails and skewness components. The initial improvement would be to use the t-distribution, instead of the Normal distribution, since it has larger tails. However, the symmetry assumption still holds, inducing underestimation of the losses in the lower tail. Furthermore, as established by [Jorion, 2010], the lack of constraints for higher losses can lead to an overestimation risk for higher confidence levels, while it's instability makes it unavailable to use for more distant forecast periods. From the list of the improvements over the t-student distribution in Figure 1.2, the skewed generalized t-distribution (SGTD) achieves the best results, in terms of accuracy of tail risk estimates, and in the incorporation of the asymmetry in the

Figure 1.2: Classification and comparison of different methods of VaR estimation



Source: Figure 3 in [Chakraborty et al., 2021].

distribution, as documented by [Lin and Shen, 2006] and [Maghyereh and Awartani, 2012]. However, [Polanski and Stoja, 2010] finds that the Gram and Charlier (GC) expansion outperforms the skewed generalized t-distribution (SGTD) method for VaR estimations, for medium to higher tails, while [BenSaïda and Slim, 2016] detect that, for equity indices, the Generalized Hyperbolic (GH) distribution performs better than the skewed generalized t-distribution (SGTD). Nonetheless, it seems that, for exchange rates, the skewed generalized t-distribution (SGTD) is still the best option. Regarding the mixture of distributions method (either from Normal or t-student distributions), [Alexander and Lazar, 2006] note that these methods are pretty accurate. [Xu and Wirjanto, 2010] show that the models with a combination of the Garch with a mixture of Normals achieve better estimates for the VaR than the combination of the Garch with either a Normal or t-student. This is further improved if the combination is with a non-linear Garch and mixture distribution (see [Nikolaev et al., 2013]), or with the combination with skewed and large tailed mixture distribution (see [Alexander and Lazar, 2006]). For the 3^{rd} strand of the parametric approach, the goal is to improve the standard Normal distribution by the inclusion of higher moments (more specifically, the skewness and the kurtosis). Although some benefits have been achieved (for example the Cornish-Fisher VaR decreases the artificially high returns of hedge funds/ institutional investments, as explained by [Boudt et al., 2013]), one main problem seemed to have risen with these approaches, regarding non-monotonicity of the Cornish-Fisher VaR estimates, that is, that higher tails result in lower values, verified in empirical studies like [Tesfalidet et al., 2014]. The main issue seemed to revolve around the choices for the skewness and kurtosis parameters to match the empirical data, which were initially incorrectly chosen. Nevertheless, this issue has been solved in other studies, including [Chernozhukov et al., 2010], who expanded the options for the choice of parameters that match the data.

As for the semi-parametric, the standard method is the Monte Carlo Simulations, which has incorporated some improvements to increase its accuracy over the years: the Delta-Gamma expansion by [Pritsker, 1997] (using full repricing in options); the Importance Sampling and Stratified Sampling by [Glasserman et al., 2002]; the Bootstrapped Algorithm by [Siegl and West, 2001]; the Principal Component Analysis by [Antonelli and Iovino, 2002]; the Fourier Transform by [Jin and Zhang, 2006]; and the Convex Conservative Approximation by [Hong et al., 2014]. In addition to this method, other semi-parametric improvements have been considered, including the Filtered Historical Simulation framework, the conditional quantile method, and the extreme value theory approach. The conditional quantile regression is focused on modelling the quantiles of the distribution of returns directly, instead of the entire distribution. This can also be related to the CaViaR approach, which we will also address later on. [Bao et al., 2006] and [Polanski and Stoja, 2010] identify that the initial symmetric version of this approach is able to better capture the empirical series behaviour during stable periods, but that diminishes during unstable periods. Nevertheless, later versions which incorporated asymmetric components greatly increased the forecasting ability of this measure, especially during turbulent periods (see [Yu et al., 2010]), and also when incorporating leverage effects and other non-linearities ([Sener et al., 2012]).

The last method within the semi-parametric approaches is the extreme value theory. The standard characteristics of this methodology within the probability, theory is to describe and forecast events that have a low probability but high consequences. The areas of application are centered on the insurance industry, portfolio optimization, and assessment of operational risk (for more detail, see [Wong, 2013]). It's main advantage is that it is able to estimate the extreme events, or the tails of the distribution, without making assumptions on the modelling process of the whole distribution itself. Not only that, it can also provide an analysis of the right and left tails of the returns distribution separately. The main limitations relate to the underlying assumptions. For example, it assumes that the extreme values ensue from identically and independently distributed (i.i.d.) samples, which conflicts with empirical evidence that returns are usually serially correlated. And although there have been techniques that have been employed to overcome this issue, there does not seem to be an agreement on which is the most suitable one. Other issues relate to the data availability selection. On one hand, the focus is on extreme events, which are rare, leading to issues with data availability. On the other hand, there is a requirement of asymptotic nature from theory. It is also sensitive to the choice of certain parameters, which can lead to bias, or errors in the estimations.

Estimations using an extreme value theory with more than 1 independent variable are more complex and more computational challenging than the univariate scenario. In terms of comparison of this methodology with the alternatives, there are several studies which evaluate this component, including [Paul and Sharma, 2017], [Chavez-Demoulin et al., 2014], [Tolikas, 2008], [Kuester et al., 2006], [Longin, 2000], and others. The main findings are that this method achieves preferable outcomes over the Normal, t-student, Historical and Monte Carlo simulations, as well as the Generalized Error Distribution, or the Skewed Generalized Error Distribution, even more so for larger tails of the distribution. They also point to the Generalized Pareto distribution and the Generalized Extreme Value distribution providing positive and similar results in terms of VaR backtesting and fitting of the returns distribution. The last result points to the similarity in terms of forecast accuracy between the Filtered Historical Simulation and the Extreme Value Distribution. In terms of the overall fitting assessment of the estimated distribution with this method and the empirical distribution, [Walls and Zhang, 2006] find that the Generalized Pareto distribution is preferable to the Generalized Extreme Value distribution. More recent studies find that the generalized Logistic distribution achieves even better estimations, as explained by [Tolikas, 2014], [Tolikas and Gettinby, 2009], and [Tolikas, 2008].

Finally, we address the non-parametric approaches, starting with the Peaks Over Threshold method. As we can see in Figure 1.2, there are 2 main strands within this method: the Hill estimator, which attempts to characterize the empirical distribution using the theoretical Generalized Pareto distribution, and the Pickland estimator, which resorts to non-parametric estimators for the fat tails index. The main conclusions for the Hill estimator suggest that the estimates for the tails of the distribution are more conservative than those obtained by the Generalized Pareto distribution, but also with lower accuracy, but still preferable to the Historical Simulation (this is confirmed by [Straetmans et al., 2008], [Bhattacharyya and Ritolia, 2008], [Walls and Zhang, 2006], [Bao et al., 2006], [Gencay and Selcuk, 2004], and others). This estimator was initially introduced by [Hill, 1975], and was later on modified by [Huisman et al., 2001], which lowered the small sample size bias for these extreme events. [Bao et al., 2006] concluded that the Hill estimator, as well as the Generalized Pareto distribution and the Generalized Extreme Value distribution perform very well during periods of financial or market distress, and are very similar to the conditional quantile estimator. [Straetmans et al., 2008] show that new sectors (for example, connected with recent technologies) are more exposed to extreme market risk and correlated market risk than older sectors (including traditional banks or insurances). For the Pickland estimator, they point to this estimator being preferable over the Historical Simulation, the Monte Carlo Simulation, and the skewed GARCH estimators for the VaR, as described in [Kellner and Rösch, 2016], [Karmakar, 2013], [Chan and Gray, 2006], [Brooks et al., 2004], and [Muela et al., 2017]. Additional contributions include the consideration of long memory and volatility asymmetry process that improve the accuracy of VaR estimates (see [Youssef et al., 2015]), [Chan and Gray, 2006] also include asset price seasonality, while [Liu et al., 2018] add jumps in conditional volatility. [Muela et al., 2017] noted that the forecast estimates for the VaR when using the Generalized Pareto Distribution are more precise and stable than the Cornish Fisher estimator.

For a briefer summary of the application of the different estimation methods in the literature, we also lay out the information in Figure 1.3, which is present in [Abad et al., 2014]. The VaR approaches included in the Figure are the following: Historical Simulation (HS); Filtered Historical Simulation (FHS); Riskmetrics (RM); Parametric Approaches estimated under different distributions, including the normal distribution (N), t -Student distribution (T), skewed t-Student distribution (SSD), mixed normal distribution (MN); high-order moment time-varying distribution (HOM); Extreme Value Theory (EVT); CaViaR method (CaViaR); Monte Carlo Simulation (MC); and non-parametric estimation of the density function (N-P).

As we have seen throughout the section, the VaR is widely used as a measure for risk in extreme negative scenarios affecting financial institutions, and has been thoroughly evaluated by academic researchers, and has been applied by financial supervisory and regulatory authorities, in order to provide an accurate assessment of risk taking by financial institutions, and the impact on the financial system as a whole. However, as described by [Adrian and Brunnermeier, 2016], one of the main issues with the VaR is that it focuses on the risk of an individual institution *in isolation*. However, a single institution's risk measure does not necessarily reflect its connection to overall systemic risk. Some institutions are individually systemic (they are so interconnected and large that they can generate negative risk spillover effects on others). Similarly, several smaller institutions may be systemic as a herd (being exposed to the same market, like the housing market), and they can exert a sort of "domino effect" on each other, amplifying the risk on the whole system. Therefore, the probabilities of these institutions being in financial distress at the same time are higher than just the product of the individual risk. These effects are not captured by the VaR, which can be seen as a measure of individual risk.

Figure 1.3: Overview of papers that compare VaR methodologies

	HS	FHS	RM	Parametric Approaches					ETV	CaViaR	MC	N-P
				N	T	SSD	MN	HOM				
Abad and Benito (2012)	x		x	x	x				x		x	
Ergun and Jun (2010)				x	x	x		x	x			
Nazori et al. (2010)		x							x			
Polansky and Stoja (2010)			x	x	x	x		x		x		
Brownless and Gallo (2010)	x		x	x								x
Huang(2009)	x			x							x	x
Marimoutou et al. (2009)	x	x		x					x			
Zikovic and Aktan (2009)	x	x		x					x			
Angelidis et al. (2007)		x		x	x	x			x			
Ozun et al. (2007)				x	x	x			x			
Tolikas et al. (2007)	x			x					x		x	
Alonso and Arcos (2006)	x	x		x	x							
Bao et al. (2006)	x	x	x						x	x	x	x
Bhattacharyya and Ritolia	x			x					x			
Kuester et al. (2006)	x	x		x	x	x	x		x			
Bekeiros et al. (2005)	x		x	x	x				x			
Gençay and Selçuk (2004)	x			x	x				x			
Gençay et al. (2003)	x			x	x				x			
Darbba, G. (2001)	x			x					x			
Danielson and Vries (2000)			x	x	x				x			

Source: Table 1 in [Abad et al., 2014]. **Notes**: In this table, there are some empirical papers involving comparisons of VaR methodologies. The VaR methodologies are marked with a cross when they are included in a paper. A shaded cell indicates the best methodology to estimate the VaR in the paper, according to the authors.

1.2.2 Quantile regressions

Linear Regression Models (LRM) vs Quantile Regression

In this section, we review the literature on quantile regressions, which is the method we use to estimate the VaR and the CoVaR.

In statistics, regressions have been used over the last 200 years to explain the relationship between the outcome (the dependent variable) and the covariates (the independent variables). Linear regressions are amongst the instruments that are mostly used to capture these effects, at the mean level, with Ordinary Least Squares (OLS) being the simplest and most common method used. More specifically, for i observations in the sample, and K independent variables we can define the linear regression model as:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_K x_K + u_i \tag{1.1}$$

where u_i corresponds to the unobserved error term. Using OLS, the procedure simply consists of estimating the K different coefficients β such that it minimizes the sum of squared residuals:

$$\hat{\beta} = arg \min_{\{\beta \in \mathbb{R}^k\}} \sum_{i=1}^{N} (y_i - x_i' \beta)^2 \tag{1.2}$$

This optimization procedure returns each of the β that captures the mean effects of each of the x_K independent variables on the dependent variable y. The use of this traditional method requires the assumption that the effects of the independent variables (or the estimated coefficients) are constant across the different elements within the sample or the population. In more recent years, there has been an increase in the interest by economists, researchers, and policymakers to evaluate the differences of the elements that compose the sample or the population, beyond just the average effects. The traditional linear regressions are not able to meet these requirements.

On the other hand, quantile regressions are able to fulfil them, by either complementing or improving the traditional method. The initial works on quantile regressions are given by [Bassett and Koenker, 1976] and [Bassett and Koenker, 1978], who first established the statistical properties using this estimation method. The main objective was to estimate conditional quantile functions, that is, to be able to define the quantiles of the conditional distribution of the dependent variable as a function of the observed variables. These quantiles are, basically, a set of "cut-off" points that divide the whole sample distribution into different groups, and each group should contain (as far as possible) an equal number of observations. This implies that the q^{th} quantile corresponds to the value of the distribution of the dependent variable for which the proportion of the sample/population that is below that same value is equal to q. For example, the median corresponds to the quantile q = 0.5, where we have 50% of the observations from the sample/population that are below that value, and 50% that are above. In this case, the sample would be divided into 2 subsamples, according to the median, or the quantile q = 0.5[3].

The segmentation into different quantiles cannot be made according to the unconditional distribution, followed by using the least squares approach on each quantile, since this would constitute an issue of sample selection (as exposed in [Heckman, 1979]). Instead, the segmentation into different quantiles conditional on the independent variables is valid (according to [Koenker and Hallock, 2001]). This method also requires that the dependent variable, y, has a distribution with relatively considerable variation, and cannot be used in cases where the dependent variable is either binary, or categorical.

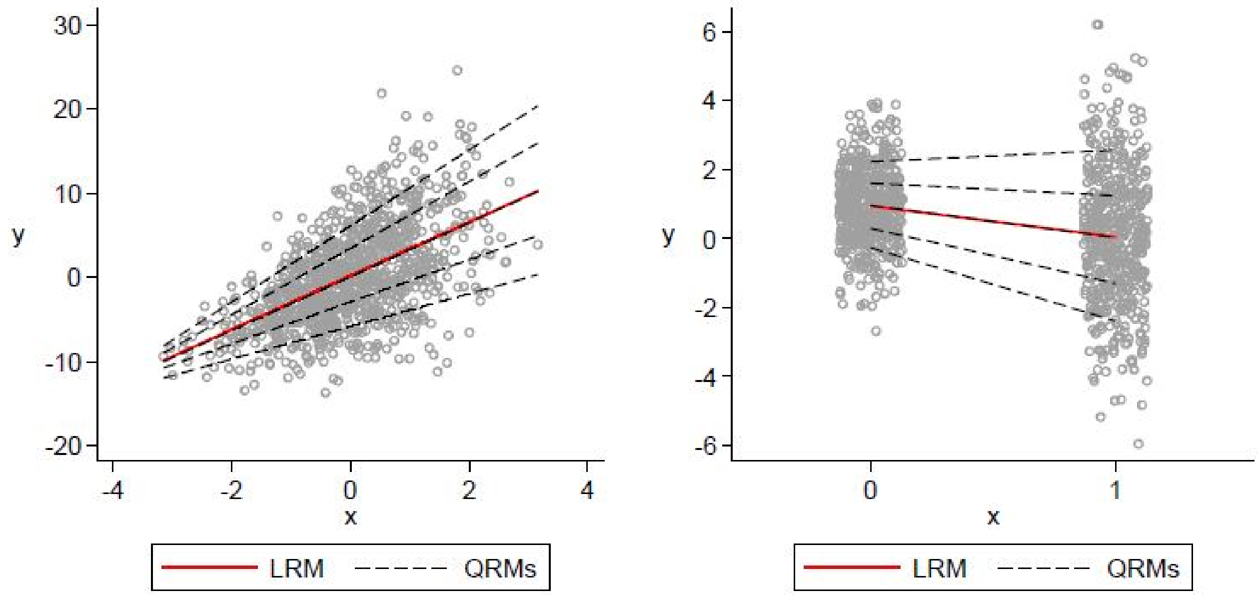
We should also consider that some of the assumptions and limitations of the linear regression method are still present in the quantile regression method. In addition to the conditional component we explained before (that is, we estimate the conditional quantile function of the dependent variable, y, given the independent variables, x, the same way that linear regression estimates the conditional mean function of the dependent variable, y, given the independent variables, x), both methods incorporate the zero conditional assumption: in the case of linear regressions, the estimators are unbiased and consistent as long as the $E(\varepsilon|x) = 0$, where ε corresponds to the residuals; while in the case of quantile regressions, we still need a similar assumption, specified by the $Quantile_q(\varepsilon_q|x) = 0$, which states that the estimates of the coefficients are consistent only if the q^{th} quantile of ε_q at every point of the distribution of x is equal to 0. Finally, when we focus the analysis *within quantiles*, both methods incorporate the linearity assumption, in which the dependent variable can be expressed as a linear function of the independent variables, and the error term. One possible way to incorporate non-linearities in the 2 approaches is by incorporating polynomials or dummy variables.

However, one of the advantages of the quantile regression estimation is that it introduced the possibility of non-linearity *across different quantiles*. In linear models, we are unable to estimate the different moments for each group/quantile (for example, the average). This would impose unnecessary restrictions on the model, and would increase difficulties in adaptation to the data. This is explained in a clearer way in [Mosteller and Tukey, 1977], where the authors explain that estimated regressions simply give a summary of the average of the distributions corresponding to the set of independent variables. They argued that we should go beyond, and compute different regressions for the different percentage points of the distribution, which would allow us to have a clearer picture. Finally, they expose that, just as the average gives a very reductive view of a single distribution, so does a single regression on a set of distribution. This can be observed

[3]The same reasoning can be made for other quantiles. For example, in the case of quartiles, which is q = 0.25, it would correspond to the value of the distribution where 25% of the observations from the sample/population would be below quartile. In this case, we would be able to divide the sample into 4 different subsamples: 0%-25%, 25%-50%, 50%-75%, and 75%-100%. Each quartile containing 25% of the whole sample, where, for example, the last quartile would contain the 25% of the highest values from the whole distribution. This is the same scenario for quintiles, with q = 0.20, for deciles, with q =0.10, and percentiles, with q = 0.01.

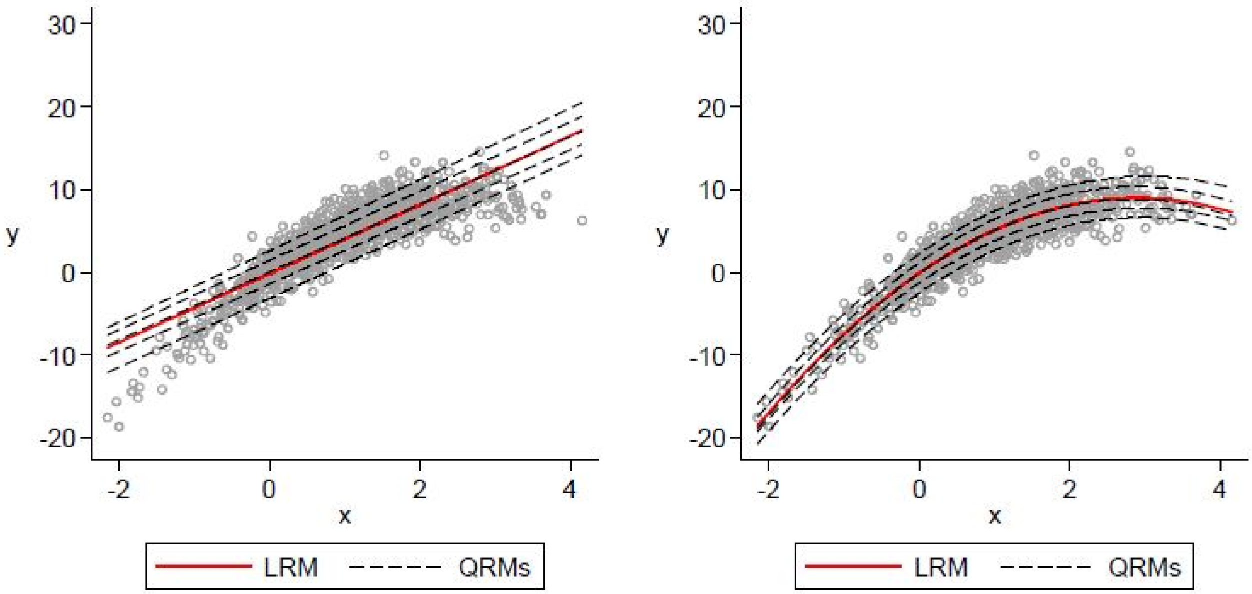
very easily in the following figures:

Figure 1.4: Comparison of linear and quantile regressions in the case of linear model with heteroskedasticity



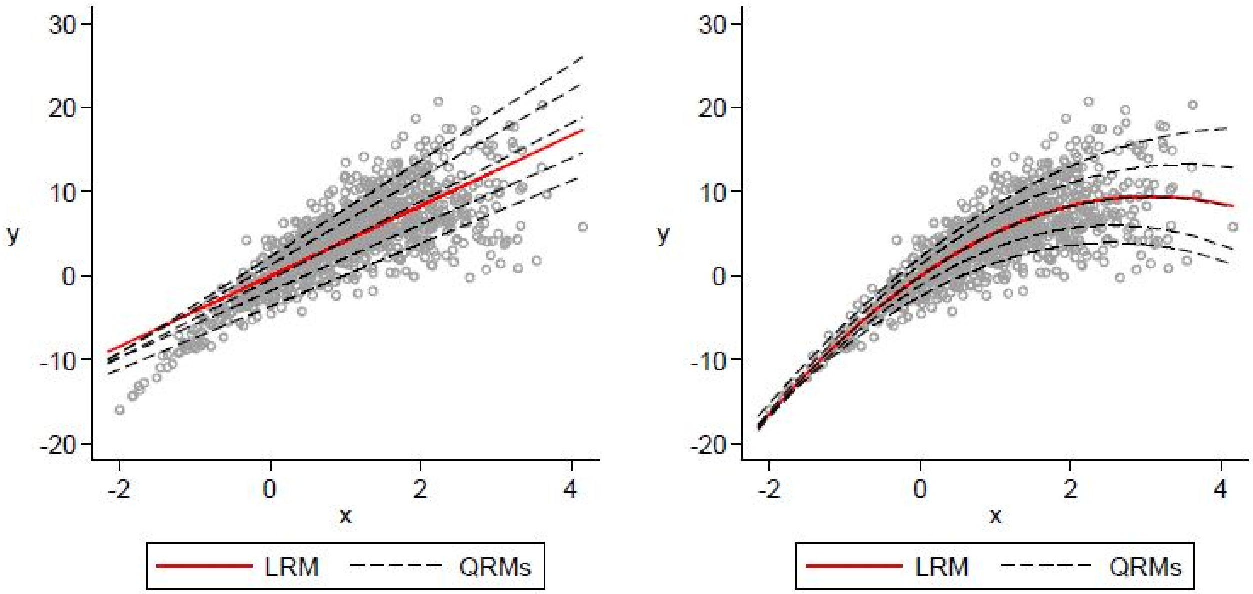
Source: In [Wenz, 2018]. Scatterplot of y against x with fit lines from LRM (solid red line) and QRMs (dashed lines) for quantiles .10, .25, .50, .75, and .90 from bottom to top. Simulated data, N=1000 randomly drawn observations. Data generating process (dgp) for left panel (scenario 1a): y = 3x + ε, where x $\sim$ N(0,1) and $\varepsilon \sim$ N(0,5 + x); dgp for right panel (scenario 1b): y $\sim$ N(1,1) for all x = 0 and y $\sim$ N(0,2) for all x = 1.

Figure 1.5: Comparison of linear and quantile regressions in the case of non-linear model with homoskedasticity



Source: In [Wenz, 2018]. Scatterplot of y against x with fit lines from LRM (solid red line) and QRMs (dashed lines) for quantiles .10, .25, .50, .75, and .90 from bottom to top. Simulated data, N=1000 randomly drawn observations. Data generating process for both panels: y = $6x$ $-x^2 + \varepsilon$, where x $\sim$ N(1,1) and $\varepsilon \sim$ N(0,2). Left panel shows fit lines for incorrectly specified models leaving out x^2(scenario 2a); right panel shows fit lines for correctly specified models including x^2 (scenario 2b).

Figure 1.6: Comparison of linear and quantile regressions in the case of non-linear model with heteroskedasticity



Source: In [Wenz, 2018]. Scatterplot of y against x with fit lines from LRM (solid red line) and QRMs (dashed lines) for quantiles .10, .25, .50, .75, and .90 from bottom to top. Simulated data, N=1000 randomly drawn observations. Data generating process for both panels: y = $6x$ $-x^2 + \varepsilon$, where x $\sim$ N(1,1) and $\varepsilon \sim$ N(0,2+x). Left panel shows fit lines for incorrectly specified models leaving out x^2(scenario 3a); right panel shows fit lines for correctly specified models including x^2 (scenario 3b).

As we can see, we have 3 different scenarios for the comparison: 1 - the case for a linear model with heteroskedasticity; 2 - the case for a non-linear model with homoskedasticity; 3 - the case for a non-linear model with heteroskedasticity. In all 3, we have the different observations represented by the grey dots, the estimation for the linear regression method (LRM) represented by the single red line in each graph, and the estimation for the quantile regression method (QRM) represented by the different dashed lines, for the different quantiles.

If we begin with figure 1.4, for example, the linear regression method takes a single estimation around the mean of the overall observations, while the quantile regression method takes several different linear regressions for the different quantiles/elements of the overall observations. On the left panel, we have a standard scenario, while in the right panel, we have a proxy for a treatment effect or experimental study scenario. In this case, we still have linearity within each estimation/quantile, but not between the different estimations/quantiles (notice that the slopes for each quantile will be different between each other), reflecting the different impacts the independent variable, x, can have on the dependent variable, y. The different impacts can be summarized according to the different positions/quantiles in the distribution. For example, the regression coefficient of the 25^{th} quantile of the distribution (which should be the second lowest dashed line) will be lower than the regression coefficient of the 75^{th} quantile (which should be the second highest dashed line).

We are also able to see that the quantile regression method is more beneficial compared with the linear regression method in the presence of heteroskedasticity, by comparing the left panels of Figure 1.4 and Figure 1.5. Notice how the linear regression is not able to capture the heteroskedasticity component (the two estimations seem to be very similar), while there is a clear difference in the quantile regression estimations, and it is able to capture the higher dispersion in Figure 1.4, through the higher difference between the different slopes. In terms of non-linearity, we see that there isn't a clear difference between the 2 methods, as reflected in the right panel of Figure 1.5. The non-linear component is incorporated in both methods, and we can argue that using different quantiles has the benefit of capturing some of the non-linear component through the non-linear characteristic between the different quantiles. However, by comparing the 2 panels of Figure 1.5, we can infer that the best option is to explicitly model the non-linear component. Notice that, on the left panel, even though the different quantile regressions are able to capture more information than the single linear regression, but notice how the different regressions are parallel, implying that the slope between the different quantiles is the same. The right panel shows that the incorporation of the non-linear or curvilinear component into the model is preferable to simply resorting to a linear quantile regression model in this scenario.

Finally, Figure 1.6 combines both non-linear and heteroskedastic components. Again, we can see how the quantile regression is preferable, by being able to capture the heteroskedasticity component to a much larger extent when compared to the linear regression method. Not only that, the presence of heteroskedasticity could also improve the ability of quantile regressions to capture non-linear components, to a certain degree. However, as we can see on the right panel of Figure 1.6, it would be preferable to also incorporate non-linearity into the model explicitly, in addition to using quantile regressions.

Hence, this is where quantile regressions come into place. Quantile regressions produce "snapshots" of the estimated relationship at different points of the distribution and, therefore, offer a panoramic - and yet parsimonious - way of capturing the whole distribution. In addition, as described by [Huang et al., 2017], in econometric terms, the quantile regression is also preferable to the traditional average-based estimation methods (including the weighted least squares (WLS)) in 2 aspects: 1 - it is more robust to problem specific features, including outliers, fat-tails, skewness, data breaks, heteroskedasticity, truncated-censored data, and other misspecifications in the errors, to identify heterogeneity in the effects of the independent variables on the outcome, depending on the different quantiles. More specifically, in the case of fat tails or asymmetries in the distribution, the median (which is given by the 50^{th} quantile of the distribution) is able to offer a preferable central picture than the mean in the traditional regression. Also, if there is a change of the extreme values and outliers, the coefficient estimated from the quantile regression does not change, nor does it's standard error. Thus, not only should quantile regressions be applied in the case of heterogeneity (or if there is interest to identify the heterogeneous effects within the sample), but also in cases where basic assumptions of the distribution are not fulfilled; 2 - It is also robust to applications to different types of data, whether it is independent data, or panel data, or time until event data. In the case of panel data, we have to consider the correlation of both cross-sectional component and time series component. Again, in traditional models, this issue is solved by simply focusing on the mean effects of the independent and dependent variables.

However, resorting to quantile regressions allows us to identify heterogeneity in the effects of the independent variables, describe the different changes at different quantiles of the dependent variable, and is more robust for heavy tails and outliers. In the case of time to event data, which are usually classified as duration models or survival analysis, the main goal is to evaluate the potential different impacts of the independent variables on the duration time (whether it increases or decreases the time until the event), or even the probability associated with potential different events (for example, probability of default). A clear potential source in the case of the event being a default is the different risk(s) for the different elements in the sample. The impact of independent variables may also be different according to the period/horizon for the specific event. As in the previous cases, and as in [Koenker and Geling, 2001], this duration/survival time is usually characterized by a non-normal distribution and fat tails.

We can, then, summarize the main advantages of resorting to quantile regressions, compared with the traditional methods: 1 - we are able to provide a more accurate characterization of the whole conditional distribution of the dependent variable, given the independent variables; 2 - the quantile regression maintains a linear programming representation, making its estimation relatively easy and simple; 3 - is a more robust measure to outliers and other misspecifications in the errors than the traditional models; 4 - by allowing for non-linearity between the different quantiles, it is able to capture the differences in the response of the dependent variable to changes in the independent variables, at different points in the conditional distribution of the dependent variable; 5 - it is more robust for the use of different types of data, making it more appealing to be widely use in a whole range of different models.

Estimation Methods

In terms of methodology, we again follow [Huang et al., 2017], who explain that most of the quantile regressions can be estimated by one of the following 2 methods: 1 - minimizing the weighted residuals; 2 - maximizing a Laplace likelihood function. The first method is more commonly used. It was initially proposed by the same authors, [Bassett and Koenker, 1978], and developed in subsequent publications by Koenker (see, for example, [Koenker and Hallock, 2001]). Basically, the goal is to estimate the quantiles of the conditional distribution by minimizing the weighted sum of the deviations between the observed variable and the estimated variable. The weights are attributed for the different quantiles. More specifically, if we consider our dependent variable, y, the independent variable/vector of independent variables, x, the different observations of the sample, $i = 1, 2, ..., N$, the cumulative distribution function (cdf) for the dependent variable, F_{y_i}, and the specific quantile, q (with $0 < q < 1$), the quantile regression model is given by:

$$Q_{y_i}(q|x_i) = h(x_i, \beta) \tag{1.3}$$

where $Q_{y_i}(.) = F_{y_i}^{-1}(.)$ corresponds to the inverse of the cumulative distribution function (cdf) for y_i, given the values of the independent variable x_i and evaluated at the quantile q, and h(.) being a known function. As explained before, we are able to estimate the coefficients, β, through the minimization of the residuals:

$$\sum_{i=1}^{N} \phi_q(y_i - h(x_i, \beta)) \tag{1.4}$$

The issue will be with the choice of the corresponding weights, ϕ_q. This weighting factor is usually described as a check function, and for any q $\in$ (0,1), the check function is given by:

$$\phi_q u_i = \begin{cases} qu_i, & \text{if} \quad ui \geq 0 \\ (q-1)u_i, & \text{if} \quad u_i < 0 \end{cases} \tag{1.5}$$

where $u_i = y_i - h(x_i, \beta)$. We can summarize the previous conditions into a single one, defined by:

$$\hat{\beta}(q) = arg \min_{\{\beta \in \mathbb{R}^k\}} \left[\sum_{i:y_i \geq h(x_i,\beta)} q|y_i - h(x_i, \beta)| + \sum_{i:y_i < h(x_i,\beta)} (1-q)|y_i - h(x_i, \beta)| \right] \tag{1.6}$$

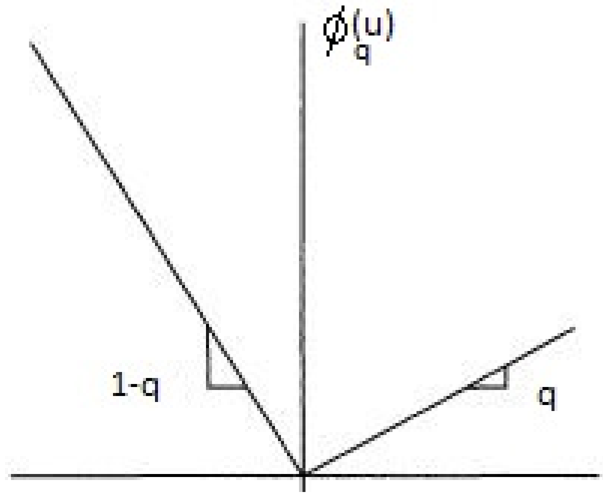
Notice the similarities between the condition (1.6) and condition (1.2). The differences consist of the estimated coefficients, β, being estimated for different quantiles, in addition to being estimated for different independent variables, x. This will affect the interpretation of the coefficients as well. In the case of OLS, the estimated coefficients reflect the change in the dependent variable due to a unit change in the independent variable associated with that coefficient. For quantile regressions, the estimated coefficients represent the change in the dependent variable due to a unit change in the specified quantile of the independent variable associated with that coefficient. However, we should be cautious with the interpretation of the coefficients, as it is possible that a change in the independent variable associated with the coefficient also leads to a change in quantile for that specific observation. More specifically, it does not mean that an observation that is in the q^{th} quantile of a conditional distribution will also be in the same quantile when the independent variable associate with that observation and with the coefficient in question changed.

Also, the estimation in quantile regressions is based on the absolute deviations between the actual and estimated values for the dependent variables, instead of the quadratic deviations in OLS. In other words, the sample mean can be seen as the solution to the problem of minimizing the sum of squared residuals, used by the linear regression method, while the median can be seen as the solution to the problem of minimizing the sum of absolute residuals, used by the quantile regression method. The sum of absolute residuals is minimized when there are an equal number of positive and negative errors that lie above and below the median line. Finally, we are also using the $h(x_i, \beta)$ function, which includes the linear case of OLS, but also allows for non-linear relationship between the $x's$ and y. Notice that, in the case of the median (with q = 0.5), the condition (1.6) becomes the Least Absolute Deviations (LAD) estimator. In this case, the weights are equal.

In addition, we can see that the quantile, q, will weigh the estimates, according to the amount of the distribution that is being used for these estimates. That is, other than the median, the different quantile functions can be obtained by giving different weights for the positive and negative residuals, or, basically, minimizing the asymmetric weight of the absolute residuals. This analysis is also provided in Figure 1.7, where ϕ_q is the tilted absolute value function that yields the q^{th} sample quantile as the solution. For example, when q is between 0 and 0.5, notice that condition (1.6) puts more weight on the right-hand side component, where we have the observations with the actual values below the predicted values, while in the case of q being between 0.5 and 1, condition (1.6) puts more weight on the left-hand side component, where we have the observations with the actual values above the predicted values. One of the advantages of this method is that it allows for higher flexibility, due to lower assumptions on the residuals. However, it could lead to difficulties in terms of the inference of the model.

The other method relates to the maximization of the Laplace likelihood function, and other parametric distributions, including infinite mixture of Gaussian densities. A detailed analysis on the asymmetric Laplace distribution (ALD) is provided in [Lum and Gelfand, 2012]. We can further subdivide this into different categories. We can start with first subcategory, in which the models begin by specifying the conditional quantile linearly in the independent variables, and then insert an asymmetric Laplace error distribution or minimize the check loss function. The model that we consider here would fall under this category, as we will discuss in more detail in sections 1.3.1 and 1.3.2. One of the earliest articles on this method is by [Yu and Moyeed, 2001], which defines a Bayesian quantile regression model, with i.i.d. asymmetric Laplace error terms, and confirm the property of the posterior of the regressors, under an incorrect prior. In general terms, we have to make some assumptions about the distribution of the variable in question (in this general example, consider y), in the sense that it follows an asymmetric Laplace distribution

Figure 1.7: Quantile regression ϕ function



Notes: Own, but similar figures in many other papers.

(ALD), and the probability density function (pdf), with parameters v, a, q:

$$f(y|v,a,q) = \frac{q(1-q)}{a} exp\left\{ -\phi_q\left(\frac{y-v}{a}\right)\right\}, y > 0, a, q \geq 0, v \in \mathbb{R}, \tag{1.7}$$

where q corresponds to the skewness parameter, a is the scaling parameter and v is the location parameter. We can identify the distribution, then, as an ALD(v,a,q). Under this assumption, we are able to say that $P_q(y \leq v) = q$ and $P_q(y > v) = 1 - q$, which implies that v is the q^{th} quantile in the ALD distribution. One possible issue could be the lack of smoothness in the ALD distribution, making it harder for the maximization of the likelihood function. However, we are able to bypass this issue, using the findings of [Kozumi and Kobayashi, 2011] and [Kotz et al., 2001], who resort to a mixture of normal or exponential distributions to estimate quantile regression models (in our model, we will consider a mixture of normal distributions), and also allow for the application of Bayesian inference, as well as likelihood-based quantile inference. [Li et al., 2010] also resorts to this kind of model, but establish priors that correspond to lasso, elastic net, and group lasso penalties. An example of a non-Bayesian application is given in [Cai and Xu, 2008], where we have linearity in the quantile, where estimated regressors are smoothed at each of several time points.

Other models within this category opt for maintaining the linearity of the conditional quantile function, although they relax the parametric assumption of the error term. Within this scenario we would find the works of [Reich et al., 2010], where the authors consider a mixture model, in which the components used for the mixing are themselves mixtures of two normal distributions, and mixing weights are used to achieve a specific quantile. [Kottas and Krnjajic, 2009] estimate the distribution of the error term of quantile regressions through two semiparametric models. [Hallin et al., 2009] consider the possibility of nonparametric conditional spatial quantile regression, concentrating on asymptotic behavior, and resorting to assumptions associated with time series asymptotics.

The next subcategory is similar to the previous one, by using the asymmetric Laplace or check loss assumption, but allows for the possibility of non-linearity in the quantiles. [Thompson et al., 2010] establish a Bayesian nonparametric quantile regression using splines. [Honda, 2004] add by also allowing for non-linearity in the parametric form of the error term.

For application of these methods to panel data models, we have the works of [Jung, 1996], who was the first to develop a quasi-likelihood process for median regression models, considering the correlation between different elements in the data. [Koenker, 2004] was able to apply his previous methods to panel data, using a penalized least squares method. Additional papers have developed on this previous approach, or presented new ones. For example, [Lamarche, 2010] has offered explanations on the specific goal of the penalized component, and methods for the choice of this element, [Galvao, 2011] has introduced dynamic components in the model, as well as instrumental variable methods for the estimation, and [Kato et al., 2012] have developed on the rate requirements for asymptotic inference, over the original model.

Nevertheless, [Arellano et al., 2017] suggest a preferable method, which involves the consideration of latent variables into the model, that is, variables that cannot be observed, but whose effects can possibly be identified on observable variables, instead of establishing the individual specific parametric effects. This approach can be seen as being based on the book of [Chamberlain, 1984], with correlated random effects for traditional mean regression methods. In terms of the estimation, they consider a modification of the expectation-maximization algorithm, similar to the one defined in [Wei and Carroll, 2009] for the latent variables, applied to cases where there are measurement errors in the estimation of the quantile regressions, due to the effects of non-observed variables being proxied by other observed variables. As expected, the main advantage of this method is to allow for the interpretation of the quantiles, conditional on the latent variables. Other estimation approaches include the Barrodale-Roberts algorithm (used by [Wang and Fygenson, 2009]), the Expectation Maximization (EM) method (see [Farcomeni, 2012]), Monte Carlo Expectation-Maximization (MCEM) approach (for example, in [Geraci and Bottai, 2007]), and the Bayesian method using Markov Chain Monte Carlo (MCMC), which can be found, for example, on [Kim and Yang, 2012]. In our model, we will also be employing the MCMC method for the estimation.

In addition to estimating specific quantiles, we could be more interested, instead, on the behaviour of the whole distribution, and estimate the $\hat{\beta}(q)$ for a wider range of quantiles. This would be preferable for a more graphical analysis, and also allows to conduct hypothesis and other inference tests at each quantile. This approach is usually referred to as the 'joint quantile model', and seems to have been initially applied by [Dunson et al., 2007], using density regressions. [Tokdar and Kadane, 2011] provides a proper joint quantile regression model, with one independent variable with finite support. Basically, the quantiles for the levels of the independent variable between the upper and lower bound values of the support are convex combinations of the cumulative distribution function at each of the boundary points. In terms of inference, [Dunson and Taylor, 2005] present an approximate likelihood method, and [Taddy and Kottas, 2010] resort to a nonparametric model which is able to derive the distribution of the independent variables, as well as the corresponding effect on the dependent variable.

Interestingly, the quantile inference ensues from the quantiles of the conditional distribution of the effect on the dependent variable, eliminating the usefulness of the estimation of the specific regressors. One of the main advantages of using this joint estimation is to avoid the issue of quantile crossing, that is, that the effect of the independent variables on the dependent variable may not be monotonic, whether increasing or decreasing. It may be the case that the true function is non-monotonic, or that there is a misspecification in the quantile regression model, or that the sample size is small. Disadvantages of this approach include the difficulty in estimation for more than 2 independent variables, the necessary restrictions on them, and the computational intensity. Following [Lamarche, 2019], the distribution for the estimated $\hat{\beta}(q)$ can be defined as:

$$\hat{\beta}(q) \sim \mathcal{N}(\beta, \frac{1}{N} q(1-q) H^{-1} J H^{-1}) \tag{1.8}$$

where $\mathcal{N}$ corresponds to the normal distribution, with J = $lim_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N} h(x_i)h(x_i)'$ and H = $lim_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N} f_i(h[x_i,\beta(q)]')h(x_i)h(x_i)'$, and $f_i(.)$ being the conditional density function of y. We can conclude 2 things from the previous formulation: 1 - the condition holds on an asymptotical level, that is, for high values of total number of observations, N; 2 - the central component is given by the conditional density function, f_i, at quantile q. This allows for the estimation in the case of heteroskedasticity. If the errors are i.i.d. (identically and independently distributed), then the conditional density function will be the same for all i units, and we can simply use the fitted value of the density at the specific quantile. The elements of the f_i function will be different amongst different i if there is heteroskedasticity. More detail on the estimation of these matrices in this scenario is provided in [Koenker, 2005].

Alternative methods that bypass the estimation of these matrices are provided in [He and Krishnamurthy, 2018], mostly consisting of bootstrap resampling methods, as well as application of these alternative estimation procedures in cases of shocks with correlation within groups (with clustered inference), and with heteroskedasticity, displayed in more detail in [Hagemman, 2017]. In the case of our model, since we are more concerned with tail risk, it would make more sense for us to focus on specific quantiles, instead of a wider range. Even though we are considering different scenarios for the extreme scenarios (either 1% of largest losses, or 5% of largest losses, or others), and not just a single one, still would not justify to shift the focus towards the whole distribution. Nevertheless, we additionally show estimations for different quantiles (more specifically, for 25%, 50% and 75%), which we explore in more detail in subsection 1.6.4. Finally, there are other elements of estimation of quantile regressions, including quantile treatment effects, measurement errors, instrumental variables, endogeneity, causality, regression discontinuity, among other, which we will not address here, since this is not applied in the case of our model. More detail on papers addressing these different components can be found on [Clarke et al., 2021], or [Koenker, 2017].

Quantile regressions are also more robust in the cases of data censoring and missing data. Given the likelihood that datasets exhibit some form of censoring (especially duration data), this aspect gives even more relevance to the use of quantile regressions. As shown by [Powell, 1986], quantile regression could be adjusted to different forms of fixed censoring, making it possible to relax the constraining conditions imposed by earlier Gaussian likelihood methods. This has been applied in other fields, for example, in biostatistics, by [Portnoy, 2003], who generalized the Kaplan-Meier estimator[4] to a regression formulation. This indicator has been used in economics as well, for example, to measure the length of unemployment, as described in [Meyer, 1990]. A relatively similar procedure was offered by [Peng and Huang, 2008] for the Nelson-Aalen estimator[5]. More recently, other papers have extended these procedures to other areas, including competing risks, recurrent events, and double censoring (see, for example, [Li and Peng, 2017]). Due to the similarities between censored data and missing data, [Yang and He, 2016] have extended this methods to include an extensive diversification of censored quantile regression models, including missing data scenarios. According to [Koenker, 2017], this type of approach is quite promising, especially for settings like interval censoring that seem otherwise quite intractable.

In terms of application of quantile regressions in other areas, even after 40 years of the initial paper's by [Bassett and Koenker, 1978], we find that this is still a very active area of research, with these estimation methods being used extensively (also as in [Koenker, 2017]). For example, [Girma and Gorg, 2002] resort to quantile regressions to evaluate the impact between Foreign Direct Investment (FDI) and economic growth, as well as investment treaties and regulations, while [Okada and Samreth, 2012] studied the relationship between FDI and corruption. We find more extensive research using quantile regressions on wages distribution and wealth inequality. For example, [Machado and Mata, 2005] attempt to decompose the changes in the distribution of wages, resorting to this method. [Buchinsky, 1995] also focuses on the wage structure, between 1963 and 1987, and was able to provide a full analysis for the impacts over different periods, according to different levels of education, and number of years of professional experience in different quantiles of the wage distribution. [Chernozhukov, 2004] provides an

[4]The Kaplan–Meier estimator, also known as the product limit estimator, is a non-parametric statistic used to estimate the survival function from lifetime data. In other fields, Kaplan–Meier estimators may be used to measure the length of time people remain unemployed after a job loss, for example.

[5]The Nelson-Aalen estimator is a non-parametric estimator of the cumulative hazard rate function in case of censored data or incomplete data.

analysis for the effects of the 401(k) program participation on the wealth distribution. A higher focus in wage and wealth inequality is given in [Melly, 2005a], and within this inequality, specific elements were evaluated, including inequality between men and women (see [Buchinsky, 1998]), differences between public and private sector (which can be found in [Melly, 2005b]), divergences between urban and rural areas (as in [Nguyen et al., 2007]), and the transmission of earnings between different generations ([Eide and Showalter, 1999]). In the topic of education, [Buchinsky, 2002] studies the return of education for women in the United States. [Eide and Showalter, 1998] evaluates the effects of the choice of school and its quality on the performance, ability and results of the students. Other studies focused on the relationship between technology and innovation and firm's size and development (see [Coad and Rao, 2008]), and the connection between efficiency in the production process and ownership by foreign entities (as in [Dimelis and Louri, 2002]). More closely related with financial topics, we find some research on capital structure (as in [Fattouh et al., 2005]), and also on house prices, as can be seen in [Zietz et al., 2008]. There is also the study by [Schaeck, 2008], in which the author uses quantile regressions to connect the structure of banks' liabilities with the time for defaults. [Chen et al., 2021] provides the estimation and inference of linear quantile regression models with general semi-parametric generated regressors. This type of regressors are used in the case of unobservable variables, for which proxy variables are resorted to.

The same initial properties were derived by [Chernozhukov, 2005], but for the extreme scenarios (the VaR and CoVaR can also be included in this type of scenario, since these are estimations of extreme losses). [Chernozhukov and Umantsev, 2001] and [Chernozhukov and Du, 2008] relate the quantiles regression application to VaR models. This is also the case for [Taylor, 1999], [Engle and Manganelli, 2004], [Bassett and Chen, 2001], and [Taylor, 2008].

1.2.3 CoVaR

[Adrian and Brunnermeier, 2016] establish a new measure of systemic risk, CoVaR, which encompasses the change in the Value at Risk of the whole financial system, conditional on an individual financial institution being in distress. This measure provides a combination of macroprudential and microprudential perspectives, as it incorporates the individual risk of each financial institution, but also combines it with the cross-section impact of this risk into the whole financial system. The main results show the accuracy of the CoVaR in reflecting systemic risk.

Our work relates, first and foremost, to the literature on systemic risk, for which [Benoit et al., 2017] provide an extensive review. [Brunnermeier et al., 2009] establishes a blueprint of systemic risk shared by many authors. [Allen and Gale, 2004], [Lehar, 2005], and [Acharya, 2009] study the endogenous nature of systemic risk. [Shin, 2010] argues that the excessive growth in assets held by financial institutions contributes to their interconnectedness (and consequently systemic risk). [Borio, 2011] highlights the 2 crucial dimensions of systemic risk: the time dimension, referring to the aggregate accumulation of risk in the financial system over time; and the cross-sectional dimension, the distribution of the risk across financial institutions at a point in time. [Elsinger et al., 2013] provide an overview of network models used to evaluate systemic risk, while [Bisias et al., 2012] encompasses a survey with 31 prevailing quantitative approaches to measure it. [Borio et al., 2001] investigate the origin of procyclicality of financial systems. The authors identify a number of potential reasons underlying such phenomena: disaster myopia; cognitive dissonance; herd behavior; shortcomings from contractual arrangements; and the inappropriate decisions of agents in the market which are caused by incomplete information. [Brunnermeier and Sannikov, 2014] defined the term 'volatility paradox' to refer to the endogenous excessive risk taking by financial institutions when volatility is low.

Some literature on contagion and spillover effects can also be linked to the CoVaR. [Hartmann et al., 2004] resort to a measure of contagion that focuses on extreme events. [Brunnermeier and Sannikov, 2015] focus on fire-sales externalities in an international model. Externalities through borrowing constraints are evaluated by [Caballero and Krishnamurthy, 2004], [Lorenzoni, 2008], and [Stein, 2009]. A strand of the literature studies potential reasons behind the fire-sales effect, more specifically, the margin/haircut spiral and precautionary hoarding behaviour, initially outlined by [Brunnermeier and Pedersen, 2009], [Adrian and Boyarchenko, 2012], [Adrian and Shin, 2010] and [Adrian et al., 2014]. [Borio, 2004] discusses the procyclical nature of the haircut/margin spirals, and [Allen et al., 2012] explore network effects as a potential source for these spillovers.

Alternative entity level measures of systemic risk have also been considered in the literature. [Acharya et al., 2017] resort to the systemic expected shortfall (SES), which measures the expected loss for each individual financial institution, conditional on the entire system being in distress, or having a high level of losses, while [Huang et al., 2012] propose the distressed insurance premium (DIP), which measures the insurance premium required to cover distressed losses in the banking system. [Billio et al., 2012] apply these three measures (CoVaR, SES and DIP) to a sample of returns composed of 4 different sectors: hedge funds, banks, broker/dealers, and insurance companies. They conclude that these sectors are highly interconnected, and that banks are the main transmitter of the shocks to the rest of the economy. [Brownlees and Engle, 2016] and [Acharya et al., 2012] lay out the systemic risk index (SRISK), which calculates capital shortfall of individual institutions, conditional on the whole system being in distress. [Lin et al., 2018] consider the marginal expected shortfall (MES), the systemic risk index (SRISK), and the Conditional Value-at-Risk (CoVaR), and find empirical evidence that systemic risk contributions are closely related to certain institution characteristic factors. [Corsi et al., 2018] resort to Granger causality tail risk networks to measure the propagation of financial distress, while [Giglio, 2016] uses a nonparametric approach to obtain bounds of systemic risk from Credit Default Swap (CDS) prices (this measure was initially developed by [Huang et al., 2012]). [Engle and Manganelli, 2004] proposed an alternative measure to the VaR, defined as CAViaR, which is a conditional autoregressive Value at Risk, and find empirical support in favour of this measure, while [Manganelli et al., 2015] provide an extension of CAViaR, which can be used to generate a dynamic version of CoVaR. [Brownlees and Engle, 2016] resort to GARCH models to estimate systemic risk. Finally, another strand of the literature uses contingent claims analysis to measure systemic risk. The first studies on this measure include [Lehar, 2005] and [Bodie et al., 2007], while [Segoviano and Goodhart, 2009] expand this approach to the global banking system.

Several papers propose extensions to the CoVaR in [Adrian and Brunnermeier, 2016]. [Adams et al., 2014] develop a state-dependent sensitivity value-at-risk (SDSVaR) approach that quantifies the direction, size, and duration of risk spillovers among financial institutions; [Wong and Fong, 2011] resort to the CoVaR to estimate the Credit Default Swap (CDS) of Asia-Pacific banks; [Gauthier et al., 2012] apply this measure to identify exposures of the Canadian banking system to systemic risk; [Hautsch et al., 2015] make use of the CoVaR to measure systemic risk within financial networks. [Castro and Ferrari, 2014] focus on the ranking component of financial institutions, according to their contribution for systemic risk.

Regarding alternative estimation approaches, [Bianchi and Sorrentino, 2020] estimate the CoVaR using 3 different methodologies: the quantile regression; a closed form formula; and a non-parametric method, finding the results to be relatively similar between the different approaches. [Oh and Patton, 2017], [Mainik and Schaanning, 2012] and [Bernardi et al., 2017] use copulas for the estimation of the CoVaR, in order to compare different systemic risk measures, including CDS (Credit Default Swap) spreads. One of the advantages of the copulas' methodology is to be able to estimate the whole joint distribution of the CoVaR across different financial institutions. [Girardi and Tolga Ergün, 2013] provide a multivariate GARCH estimation of the CoVaR, while [Bernardi et al., 2013a] propose Bayesian inference. [Kibzun and Kuznetsov, 2006] compare the modelling and mathematical properties of the VaR and CoVaR. [Escanciano and Olmo, 2010] focus on quantifying estimation risk, and provide corrections measures in an out-of-sample analysis. There are also some cases using maximum likelihood methods, which require the authors to take some assumptions on the distribution. [Bernardi et al., 2013b] use this method to consider the possibility of fat tails and non-linear dependence. [Cao, 2013] resorts to his method also to estimate the whole joint distribution.

In more recent literature, there has been an application of the VaR models focusing on economic growth, Growth-at-Risk (GaR): which delivers the full density of the conditional distribution of GDP growth. [Adrian et al., 2019] discuss these types of models, and argue that the amplification mechanisms in the financial sector generate observable growth vulnerability dynamics. Supervisory and regulatory institutions, including the International Monetary Fund (IMF), have also started to consider the GaR via conditional quantile predictions in their standard monitoring toolkit (as can be seen in [Prasad et al., 2019]). [Corradi et al., 2020] propose tests for pairwise and multiple out-of-sample comparisons of parametric conditional quantile models, with an empirical application to Growth-at-Risk (GaR).

1.3 Model

1.3.1 The CoVaR

To capture time-variation in the joint distribution of losses of a given institution i and the financial system $\mathbb{S}$, [Adrian and Brunnermeier, 2016] estimate the CoVaR as a function of state variables [6]. The following equations define their model.

$$X_t^i = \alpha_q^i + \gamma_q^i M_{t-1} + \varepsilon_{q,t}^i, \tag{1.9}$$
$$X_t^{\mathbb{S}|i} = \alpha_q^{\mathbb{S}|i} + \gamma_q^{\mathbb{S}|i} M_{t-1} + \beta_q^{\mathbb{S}|i} X_t^i + \varepsilon_{q,t}^{\mathbb{S}|i}. \tag{1.10}$$

Where X_t is a time series of losses, M_{t-1} are (lagged) state variables and ε_t are innovations of the quantile regression for a given quantile q. The authors then use the predicted values of equations (1.9) - (1.10) to obtain

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1}, \tag{1.11}$$
$$CoVaR_{q,t}^{\mathbb{S}|i} = \hat{\alpha}_q^{\mathbb{S}|i} + \hat{\gamma}_q^{\mathbb{S}|i} M_{t-1} + \hat{\beta}_q^{\mathbb{S}|i} VaR_{q,t}^i. \tag{1.12}$$

The mechanics underlying the CoVaR are fairly simple. A first quantile regression (1.11) is estimated so as to obtain the q quantile Value-at-Risk for institution i. Next, the predicted value is used to estimate equation (1.12). The second quantile regression yields the CoVaR, which is a function of both the state variables and the tail risk of institution i. From the above equations it is clear that the CoVaR would be constant over time if no state variables were included in the regressions. Therefore, the dynamics of the CoVaR are entirely inherited from the dynamics of the state variables.

We argue that it is desirable to allow the parameters governing the relations between each financial institution and the financial system to vary over time. It is plausible that the importance of a specific firm changes throughout time depending on its size and risk. However, in the equations above, this relation is assumed to be constant and given by $\hat{\beta}_q^{\mathbb{S}|i}$. Moreover, there are also good reasons to believe that the link between state variables and financial firm losses may be dynamic. [Adrian and Brunnermeier, 2016] consider seven state variables which include four interest rate spreads, the market and real estate equity returns and stock market volatility. The choice of the specific variables is motivated by their relevance in capturing the conditional moments of asset returns. Financial firm's balance sheets are known to be very sensitive to the interest rate level and slope. However, the Duration gap, which measures the sensitivity a firm's asset and liability structure to interest rate changes, ought to change over time in virtue of a firm's business model or risk management decisions. Nevertheless, the link between the state variables and firm specific/financial sector tail risk is assumed constant, given by γ_q^i and $\gamma_q^{\mathbb{S}|i}$.

[6] See section C (pp.15-16) of [Adrian and Brunnermeier, 2016]

In the next sections we discuss the changes to this framework so as to accommodate time-varying parameters.

1.3.2 The Dynamic CoVaR

The following equations allow us to estimate a Dynamic CoVaR.

$$X_t^i = \alpha_{q,t}^i + \gamma_{q,t}^i M_{t-1} + \varepsilon_{q,t}^i, \tag{1.13}$$

$$X_t^{\mathbb{S}|i} = \alpha_{q,t}^{\mathbb{S}|i} + \gamma_{q,t}^{\mathbb{S}|i} M_{t-1} + \beta_{q,t}^{\mathbb{S}|i} X_t^i + \varepsilon_{q,t}^{\mathbb{S}|i}. \tag{1.14}$$

Notice that the only difference as compared to equations 1.9 - 1.10 is that all the parameters are dynamic - they are allowed to vary over time. We define the Dynamic CoVaR as

$$DVaR_{q,t}^i = \hat{\alpha}_{q,t}^i + \hat{\gamma}_{q,t}^i M_{t-1}, \tag{1.15}$$

$$DCoVaR_{q,t}^{\mathbb{S}|i} = \hat{\alpha}_{q,t}^{\mathbb{S}|i} + \hat{\gamma}_{q,t}^{\mathbb{S}|i} M_{t-1} + \hat{\beta}_{q,t}^{\mathbb{S}|i} DVaR_{q,t}^i. \tag{1.16}$$

In contrast to the CoVaR, the Dynamic CoVaR picks up two types of potential non-linearities in the relationship between institution i, the state variables and the financial sector $\mathbb{S}$. First, because $\hat{\beta}_{q,t}^{\mathbb{S}|i}$ is time dependent, the tail dependencies between the losses of institution i and the financial sector $\mathbb{S}$ are dynamic. Second, the relevance of the state variables in determining tail risk of both institution i and the financial sector at large are also dynamic. The intercepts are also time-dependent, giving the model additional flexibility in adjusting to the data.

1.4 Econometric Approach

In order to estimate the model, we base the estimation procedure according to [Bernardi et al., 2016] and [Bernardi et al., 2015] (the latter one applied to a single regressor, and the first one extended it to an entire vector of regression parameters, so they can evolve stochastically over time). Other papers, including [Koop and Korobilis, 2012] and [Koop and Korobilis, 2013] have also included time-varying components into their analysis (for example, for forecasting of inflation).

1.4.1 A Bayesian quantile regression with time-varying parameters

We estimate the *DCoVaR* with a time-varying parameter quantile regression of the form

$$y_t = \mathbf{x}_t' \beta_{q,t} + \theta z_t + \phi \sqrt{z_t} u_t. \tag{1.17}$$

$$\beta_{q,t} = \beta_{q,t-1} + v_t \tag{1.18}$$

Where $z_t \sim Exp(1)$ and u_t is a standard normal distribution. $\theta = (1-2q)/q(1-q)$ and $\phi = 2/q(1-q)$, for a given quantile $q \in [0,1]$. The law of motion of the parameters is of autoregressive form, defined by (1.18) with $v_t \sim N(0,Q)$. We follow [Kozumi and Kobayashi, 2011] in expressing a quantile regression (1.17) in such a way that its innovations u_t are Gaussian. This is licit because, since the innovations of a quantile regression in its standard form are asymmetric Laplace distributed (see [Yu and Moyeed, 2001]), they admit a scale mixture of normals representation.

It is easy to see that the DCoVaR can be represented in the form (1.17)-(1.18), with $y_t = \{X_t^i, X_t^{\mathbb{S}|i}\}$, $\mathbf{x}_t = [\mathbf{1}, M_{t-1}]$ or $\mathbf{x}_t = [\mathbf{1}, M_{t-1}, DVaR^i_{q,t}]$ and $\beta_{q,t} = [\alpha^i_{q,t}, \gamma^i_{q,t}]$ or $\beta_{q,t} = [\alpha^{\mathbb{S}|i}_{q,t}, \gamma^{\mathbb{S}|i}_{q,t}, \beta^{\mathbb{S}|i}_{q,t}]$, where $\mathbf{1}$ is a vector of ones to allow for the intercept.

The novelty of our approach lies in allowing non-linearity between the response variable and the covariates for each quantile. Therefore, the parameters $\beta_{q,t}$ are allowed to vary across quantiles q but also over time t. Our estimation strategy consists in realizing that the quantile regression admits a state space representation. Thus, the application of the Kalman filter algorithm proposed by [Carter and Kohn, 1994] is possible. In Appendix 1.10.1, we derive the full Gibbs Sampler used for posterior inference. Next, we present the priors used.

1.4.2 Priors

To proceed with Bayesian analysis, we consider the priors

$$\beta_{q,0} \sim N(0, V_0), \tag{1.19}$$

$$Q \sim \mathscr{IW}(s, w). \tag{1.20}$$

Where $\mathscr{IW}(.)$ denotes the Inverse-Wishart distribution and V_0, s, w are hyperparameters. The Normal-Wishart prior defined above offers several advantages. The full conditional densities of $\beta_{q,t}$ and Q are of standard form and are a classical choice for time-varying parameter models (see [Primiceri, 2005]). They result in a easy to implement 3 block Gibbs Sampler.

1.5 Data

Our sample comprises of the 65 largest financial institutions constituents of the S&P500 Financials, ranked according to their market capitalization, as they comprise more than 90% of the whole market. The sample period goes from 01/11/1988 until 02/11/2020[7]. The weekly market equity data is used to calculate the individual institution loss variable, X_t^i, as well as the financial system loss variable, X_t^S, where the last is generated by taking market equity losses from all institutions in our sample, weighted by lagged market equity[8].

As for the state variables, most of the information was retrieved from the Federal Reserve Economic Data (FRED), with the exception of the *weekly market returns*, which was obtained from REFINITIV. They can be described as follows:

- The *change in the three-month yield*. The change is used instead of the level, since it is most significant in explaining the tails of financial sector market-valued asset returns.
- The *change in the slope of the yield curve*, measured by the spread between the composite long-term bond yield and the three-month bill rate.
- A *short term 'TED spread'*, defined as the difference between the three-month LIBOR rate and the three-month secondary market treasury bill rate, which we use as a proxy for short-term liquidity risk.
- The *change in the credit spread* between Moody's Baa-rated bonds and the ten-year Treasury rate.
- The *weekly market return* computed from the S&P500. We retrieved the daily data for this indicator, and then collapsed into weekly data.
- *Equity volatility*, measured by the Chicago Board Options Exchange (CBOE) S&P100 Volatility Index (VXO).

The variables and intermediary calculations for the raw data follow closely to those applied by [Adrian and Brunnermeier, 2016], with the main difference being in the sources of the data. We initially resorted to daily market equity data provided by the CRSP, which would then be collapsed to weekly data. Nonetheless, due to the unavailability for periods after 2019[9], and given the potential impact of the COVID-19 pandemic in the current economic and financial environment, we opted instead to obtain weekly market equity data from REFINITIV. Finally,

[7]The reason we were not able to use previous periods was due to lack of data availability, more specifically, from the equity volatility (VXO) variable.

[8]In the case of our dataset, for the institutions where there is only data for 17/04/2000 or after, there is not enough data to make the estimations, and those institutions will only present empty values. This is the case, for example of MetLife.

[9]According to the Database for the CRSP, the information is updated on a yearly basis, in May of every year.

the list of the top 10 financial institutions we are considering in some of our figures are as described: JPMorgan Chase; Berkshire Hathaway; Bank of America; Citigroup; Wells Fargo; Morgan Stanley; Charles Schwab; S&P Global; American Express; Blackrock.

We provide a summary of statistics for the state variables in the Appendix (see Table 1.1).

1.6 Discussion of the Results

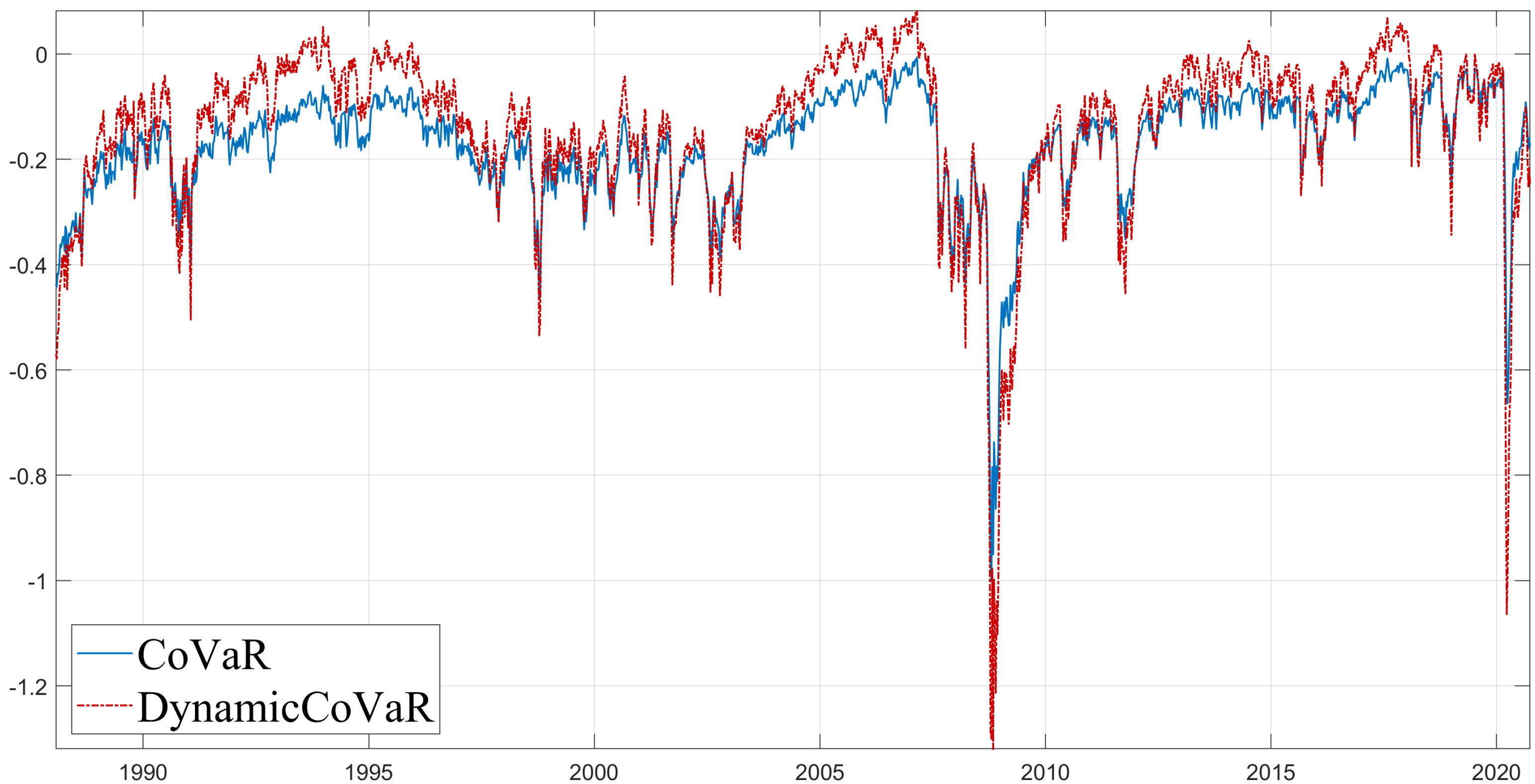
1.6.1 Measurement of Systemic risk

In Figures 1.8 and 1.22 (the second one in Appendix 1.10.2), we present our estimation for the Dynamic CoVaR (DCoVaR) and Dynamic VaR (DVaR), respectively, for a representative institution, whose equity returns are calculated as a weighted average of the top 10 firms - weighted by their market capitalization. We, then, compare these statistics with the estimation for the standard VaR and CoVaR employed in [Adrian and Brunnermeier, 2016]. As we can see, the estimation for the VaR and DVaR are exceedingly similar between the two models. Recalling that, according to [Adrian and Brunnermeier, 2016], the VaR gives the risk of individual financial institutions *in isolation*, we can infer that the dynamic component that we introduced does not affect the estimations for the risk of individual financial institutions.

On the other hand, the estimation for the CoVaR is starkly different, reflecting the influence of the dynamic component on systemic risk analysis instead. In fact, the introduction of time-varying parameters leads to an increase of the volatility of the CoVaR values in general. As we can see in Figure 1.8, the values of the DCoVaR are higher than those of the CoVaR in 'good periods', that is, when the market equity returns are higher, and the values of the DCoVaR are lower than those of the CoVaR in 'bad periods', that is, when the market equity returns are lower. Therefore, the results of our time-varying parameters seem to point to a higher procyclical component of systemic risk than in the original model. As expected, this is likely due to the introduction of additional sources of risk we mentioned before: that tail dependency between the loss distributions of the financial system and of each individual institution can change over time, as well as the effect between state variables and tail risk.

More specifically, with the introduction of the dynamic component into the model, as well as the results, we can conclude that: 1 - The changes in the impact of the state variables on individual risk over time is small (given by the low differences between VaR and DVaR, captured by the $\hat{\gamma}^{i}_{q,t}$ component); 2 - Given the significant differences between CoVaR and DCoVaR, they can result either from the changes of the impact of the state variables on the dependent variable (systemic risk) over time (the $\hat{\gamma}^{\mathbb{S}|i}_{q,t}$ component), or from the change of the impact of the individual risk of each institution on the systemic risk over time (the $\hat{\beta}^{\mathbb{S}|i}_{q,t}$ component), or a combination of both. In point 2, the first scenario would suggest that the exposure of the financial system to macroeconomic conditions changes overtime, while the second scenario would imply changes in the conditions within the financial sector itself. For example, a higher impact of the DVaR of a certain financial institution in the DCoVaR could reflect a higher relevance of a specific institution for the whole financial sector, or that the sector itself could be taking more risk, becoming more exposed to individual institutions. Finally, recall that these differences are also connected to the relaxation of some of the assumptions in the original model. Specifically, although the original model allows for non-linearities across different quantiles, it imposes linearity within each quantile. Our model accounts for the possibility of existence of non-linearity within each quantile, offering additional flexibility to reflect the ’true’ level of risk, given the data. Hence, we also argue that it is this additional flexibility of the model that leads to higher volatility, pointing to the hypothesis that systemic risk exhibits more procyclicality than that implied by the original [Adrian and Brunnermeier, 2016] model.

Figure 1.8: CoVaR Functions

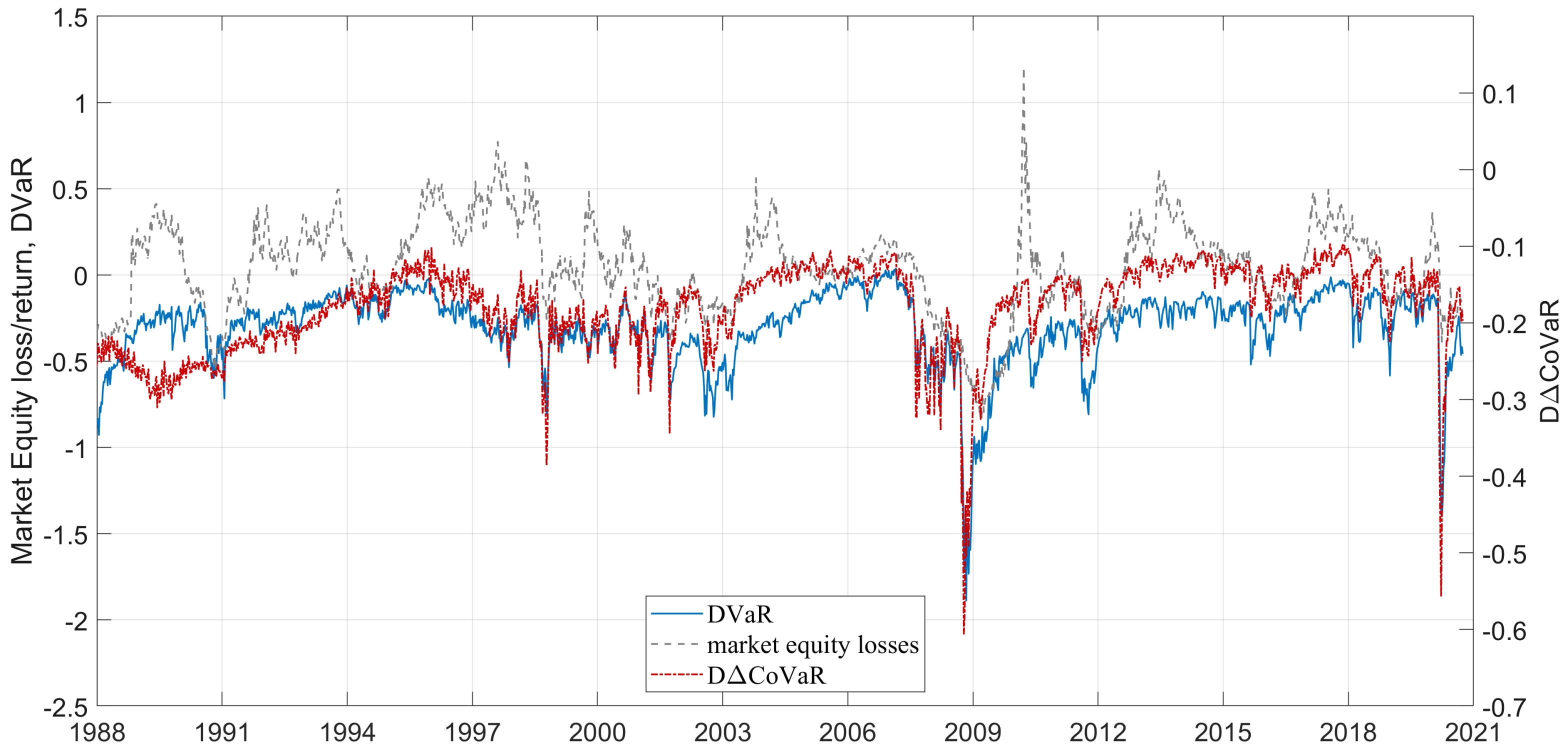


Notes: The CoVaR refers to the model of [Adrian and Brunnermeier, 2016] (blue line); The DCoVaR refers to the Dynamic CoVaR proposed in the body of the paper (red-dashed line), for the weighted-average of the largest 10 financial institutions. The variables are expressed in units of total 52 week market returns at a weekly frequency.

We proceed with a *cross-section* analysis of the average Dynamic VaR (DVaR) and Dynamic CoVaR (DCoVaR) for the sample periods, described in Figure 1.23 in Appendix 1.10.2. We can observe the absence of a relationship between these 2 variables (or a very feeble connection between them). If we recall that VaR can be interpreted as a measure of risk for an individual institution, and the CoVaR as a measure of risk for the financial system as a whole, we can conclude that establishing rules and regulations based on the individual risk may be insufficient, or ineffective, or even counterproductive, to prevent systemic risk.

When we, instead, assess the *time series* relationship between DVaR and DCoVaR in Figure 1.9, for the top 10 financial institutions in our sample, we can identify the strong link between these two measures. We can also observe the mirror image effect between both measures and the market equity losses, revealing their explanatory capabilities of actual losses. Both of the previous results (for the cross-section and time series) are similar to the ones obtained in [Adrian and Brunnermeier, 2016]. Additionally, the DCoVaR seems to achieve better results, especially in periods of crises. For example, the DVaR seems to overestimate market equity losses between 1985 and 1990, while the DCoVaR accurately shows the losses from the 2008 financial crisis. Moreover, we can clearly see the adverse effects from the more recent COVID-19 pandemic. Both the DVaR and the DCoVaR show a huge decrease in 2020, and the impact seems to be of the same dimension as the 2008 financial crisis. Although market equity losses do not seem to be affected so far in our sample, when we again compare with the behavior from the 2008 financial crisis, the spike in market equity losses only manifested after 2010, lagging behind the decrease of the DVaR and the DCoVaR in 2008.

Figure 1.9: Time-series of DVaR and DΔCoVaR for Large Financial Institutions



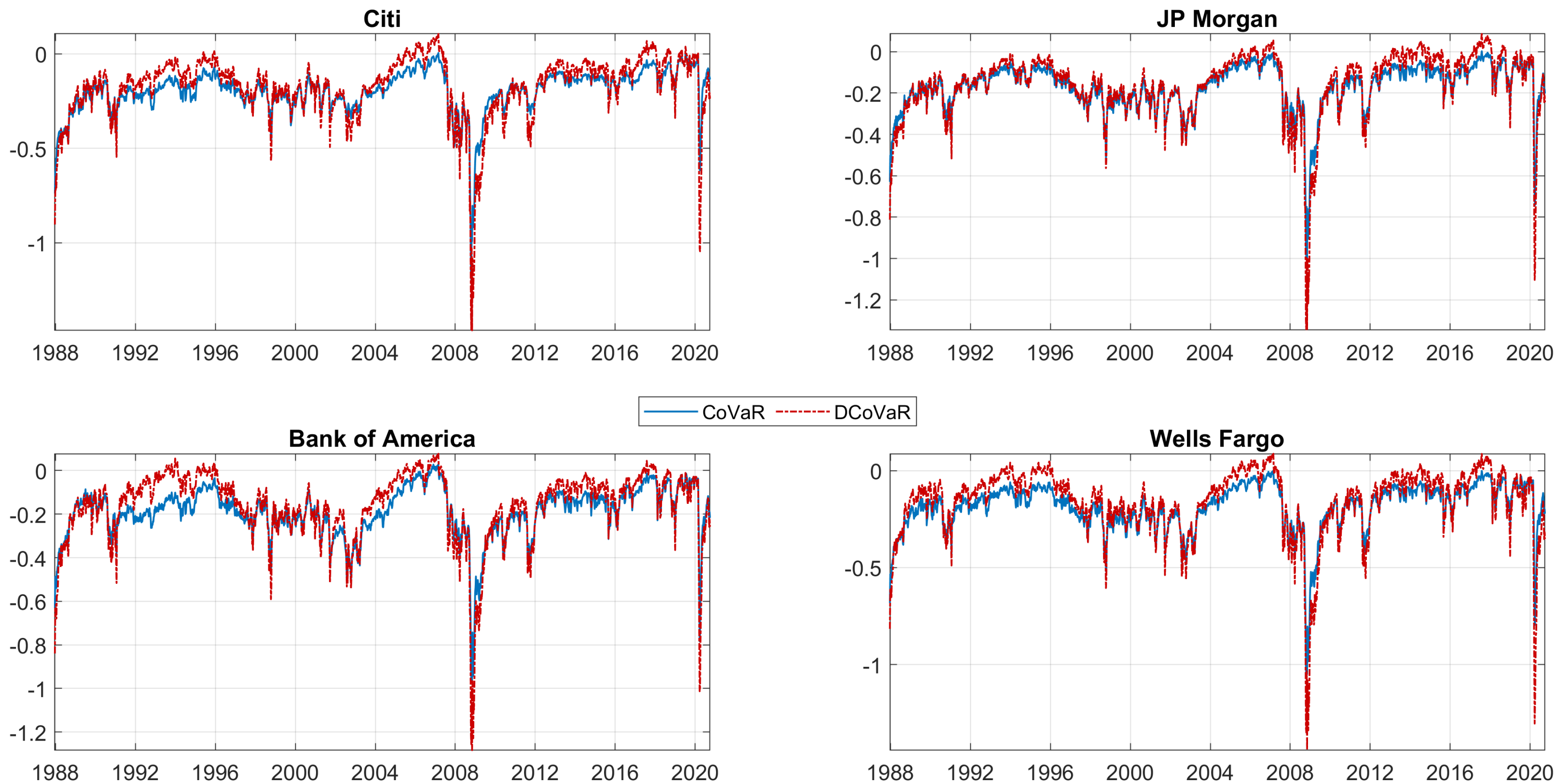
Notes: Market equity losses (gray line) are observed equity losses, the Dynamic VaR (DVaR, blue line), and the Dynamic ΔCoVaR (DΔCoVaR in red) for a sample of the largest 10 financial institutions. The variables are expressed in units of total 52 week market returns (or losses for the gray line) at a weekly frequency. The DΔCoVaR is simply the changes in the CoVaR, compared to its median state. We use it for illustrative purposes. The formula is given in Appendix 1.10.3.

Therefore, it is likely we will observe the same lagged behavior for a large increase of market equity losses due to the COVID-19 pandemic in the near future. In fact, in 2022, we saw some losses in the financial markets, as well as during 2020, however, not with the same significance and prolonged nature as the Great Financial Crisis. We argue that this results from the large and unprecedented government bailout during the COVID-19 pandemic, amounting to 4 trillion dollars. Even though this crisis did not originate in the financial sector, it would easily spread there without government assistance. However, this translated to inflation pressures, and possible losses in the future.

Lastly, we provide the comparison between the CoVaR and the DCoVaR for 4 different financial institutions, on an individual level, in Figure 1.10. The differences in the two indicators between each institution show their different impact on systemic risk, or that the whole financial sector has different levels of exposure to different institutions. We can also observe that the difference between the 2 indicators is very distinct between each institution, reflecting that the different contribution for systemic risk does not generate simply from the state variables, but also from the changing exposure of the system to individual risk. Nevertheless, notice that the main conclusions we took from Figure 1.8 are also reflected in each of the individual figures here (more specifically, the increase in volatility and procyclicality, compared with the standard model). This result seems to favour the use of the average of the top 10 firms in our results, as they seem to be representative of the financial institutions in our sample.

It is also important to point out that in this subsection, we have expressed the several variables in the same units as the market returns, for comparability with said variable, especially in the case of Figure 1.9. Henceforth, for the remaining sections and subsections, we will change our measurement to standardized units. The behaviour of the series is very similar, the difference being only in terms of the units expressed, and, as a result, the scale in the y-axis of the graph.

Figure 1.10: Time-series of CoVaR and DCoVaR for 4 Large Financial Institutions



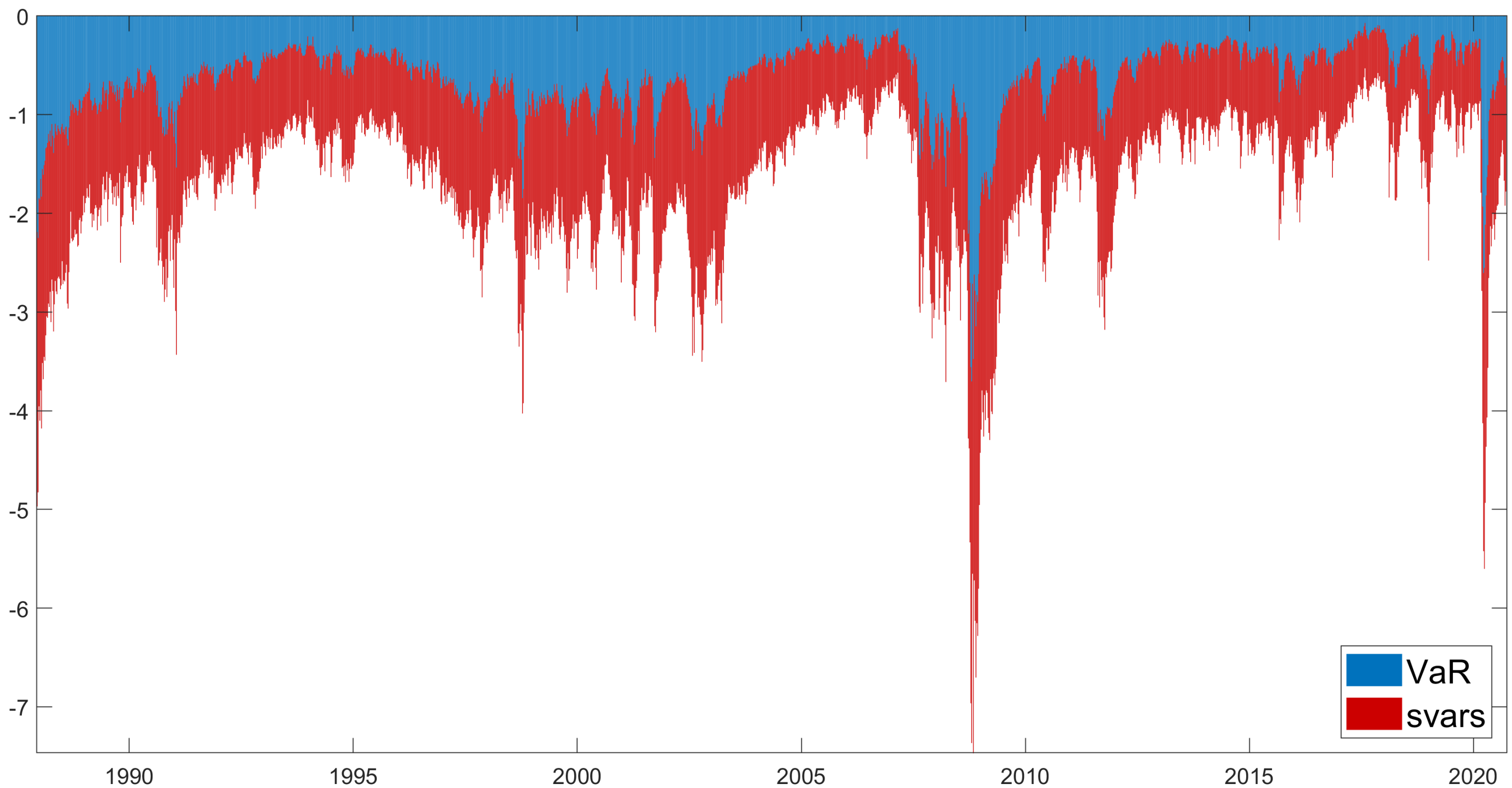
Notes: The time-series of weekly CoVaR (blue line) and DCoVaR (red line) is shown for the 4 largest financial institutions in our sample, measured by Market Capitalization as of January 2020: Citibank, JPMorgan, Bank of America, and Wells Fargo. The variables are expressed in units of total 52 week market returns at a weekly frequency.

1.6.2 Impact Component Analysis

In this section, we seek to provide a closer analysis of the different components that constituted the results in the previous subsection. More specifically, our goal is to differentiate between the effect of the idiosyncratic risk (given by the VaR and DVaR), the effect of the state variables, and the effect of the intercept. Given that the state variables comprise of 6 different variables, we will also evaluate the impact of each of them individually, for the case of our model, with the time-varying parameter component. For illustrative purposes, we show the results resorting to a stacked bar chart. We also opted not to include the impact of the intercept in the figures for either case, since the impact is either constant (in the case of the standard model), or the impact is relatively stable (which is the case of our time-varying parameter model).

We begin with the subdivision of these effects for the standard model, in Figure 1.11. The effects of the 2 components seem to be significant, although it is clear that the combined effect of the state variables is higher than the effect of the idiosyncratic risk. Recall that the VaR incorporates the impact of the state variables on the idiosyncratic risk. As a result, the 'svars' component in the figure simply reflects the direct effect on the CoVaR (since the indirect effect through the VaR is incorporated in the VaR itself). This seems to, again, point against using the VaR as a measure of systemic risk. Although the VaR should be a component of systemic risk calculation (given its significance in explaining the CoVaR), it does not even seem to be the main component, as the macroeconomic conditions (reflected by the state variables) seem to be a better predictor (given their higher relevance in explaining the CoVaR). Interestingly enough, notice that the proportion of the CoVaR that is explained by the VaR seems to increase in periods of crisis. This can be easily seen in the case of the 2008 financial crisis, where the VaR seems to explain more than half of the lowest value of the CoVaR in the sample. We can conclude that, even though the VaR should be used as measure of idiosyncratic risk, and it should not be seen as a proxy for systemic risk, it should be considered as a component for systemic risk, along with the state variables.

Figure 1.11: CoVaR components



Notes: This figure illustrates the CoVaR from the model of [Adrian and Brunnermeier, 2016]. The impact of the different components is given by the VaR (blue line); and the state variables (red line), for the weighted-average of the largest 10 financial institutions. The variables are expressed in units of total 52 week market returns at a weekly frequency (standardized).

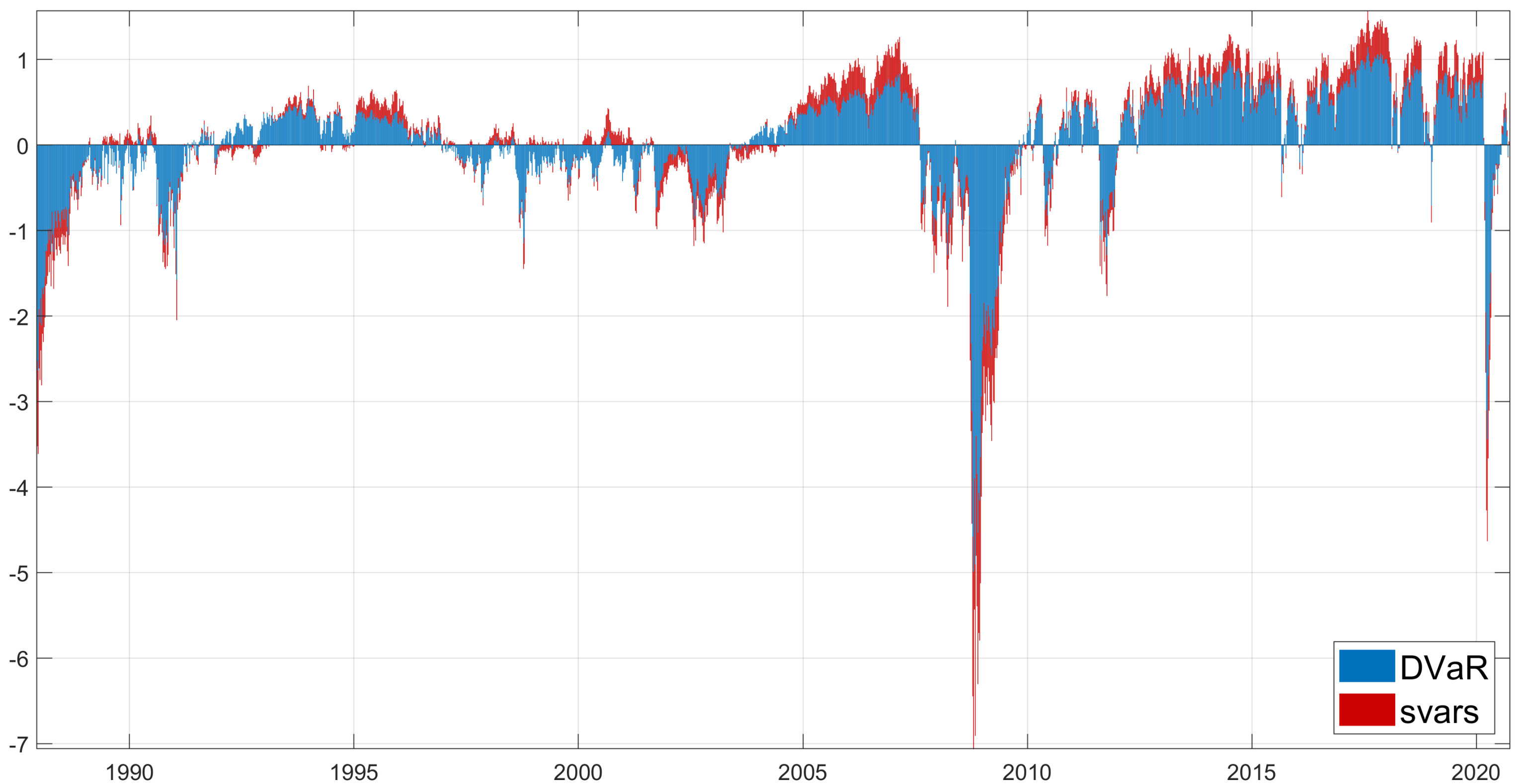
We, then, follow with the same analysis, but for our model with the time-varying parameter component, in Figure 1.12. We can identify 2 main differences when comparing with the previous results. The first one is that the impact values not only change in magnitude (either increase or decrease), but also in terms of direction (positive or negative). Before, since the estimated coefficients are constant over time, the only changes in the values of the CoVaR are due to changes in the estimated VaR and the state variables. Not only that, the changes are only in terms of magnitude (how negative the CoVaR is going to be). Since the estimated coefficients are constant, not only are they unable to change in terms of their magnitude, but also, in terms of direction. And even though some of the state variables could change direction, not only is that taken into account in the estimated value of the coefficients (possibly decreasing their magnitude when we include more observations of the corresponding variable of the opposite direction), but also it seems that the effect would be countered by the remaining variables. For example, recall that the estimated coefficients' magnitude and direction would be defined according to the average of the effects of the independent variable on the dependent variable. Even in a period where we could have an exception to the rule, and have one of the variables move in the opposite direction, making the impact on the CoVaR also move in the opposite direction, the impact of the remaining variables on the CoVaR, in each period, are such that it outweighs the initial change in the direction of the impact of the single variable.

Now, however, the ability of parameters for each independent variable to change overtime leads to changes in the magnitude, but also in terms of direction. As we can see in Figure 1.12, the values are negative, reflecting periods of severe crisis (for example, the 2008 financial crisis, or the COVID-19 pandemic), as well as other relatively mild downturns, but they can also be positive, reflecting periods of economic growth or expansion. By comparing Figures 1.11 and 1.12, we can conclude that the only possibility for the change in direction of the effects is due to the change in direction of the estimated coefficients. We can also see the results in Figure 1.12 as a reflection of the increase in volatility and procyclicality that we discussed before, and the time-varying parameter component being the central component for that result.

The second one relates to the increase in the proportion of the DCoVaR that is explained by the DVaR, when compared to the standard case of the CoVaR and the VaR. As we can see, most of the behaviour of the DCoVaR can be explained by the DVaR, instead of the state variables, which is the opposite conclusion of our initial scenario. This would seem to point that, in our model, the measure of idiosyncratic risk could be a good indicator for systemic risk as well. However, we should recall that our measure of idiosyncratic risk is fully dynamic, while the dynamic component of the idiosyncratic risk in the standard model stems only from the state variables. As a result, it seems that our estimations point to the measure of idiosyncratic risk being a good proxy of systemic risk, as long as it is fully dynamic.

We can also see that, in the vast majority of periods in the sample, the impact of both components of the DCoVaR move in the same direction. That is, within each period, in most cases, both DVaR and state variables have a positive or negative effect. In some rare cases, they move in opposite directions. For example, around 1990, most values for the impact of the DVaR are negative, but most values for the impact of the state variables are positive. This would point to a high correlation between the 2 components, which is expected to a certain degree. For example, in the case of economic expansion, reflected by positive values for the state variables, it is unlikely that financial institutions will be in financial distress individually. But even if that is the case, it is unlikely that the individual risk of said financial institution will have a high impact on systemic risk. So, either the DVaR will be low, or its impact on the dependent variable, given by the estimated coefficient, is low. Likewise, we can look at it from the opposite point of view. In the case of a significant downturn, reflected by negative values for the state variables, it is likely that this will cause a significant portion of financial institutions to enter in financial distress, leading to lower values of the DVaR, or increasing the impact of the idiosyncratic risk on systemic risk, also due to potential contagion effects, given by the estimated coefficients. Or it could be the case that an increase of idiosyncratic risk could spread to other financial institutions (due to their size, for example), leading to an increase of the DVaR or its systemic impact, and this could easily spillover to other sectors in the economy, whose effects are reflected by the state variables.

Figure 1.12: DynamicCoVaR components

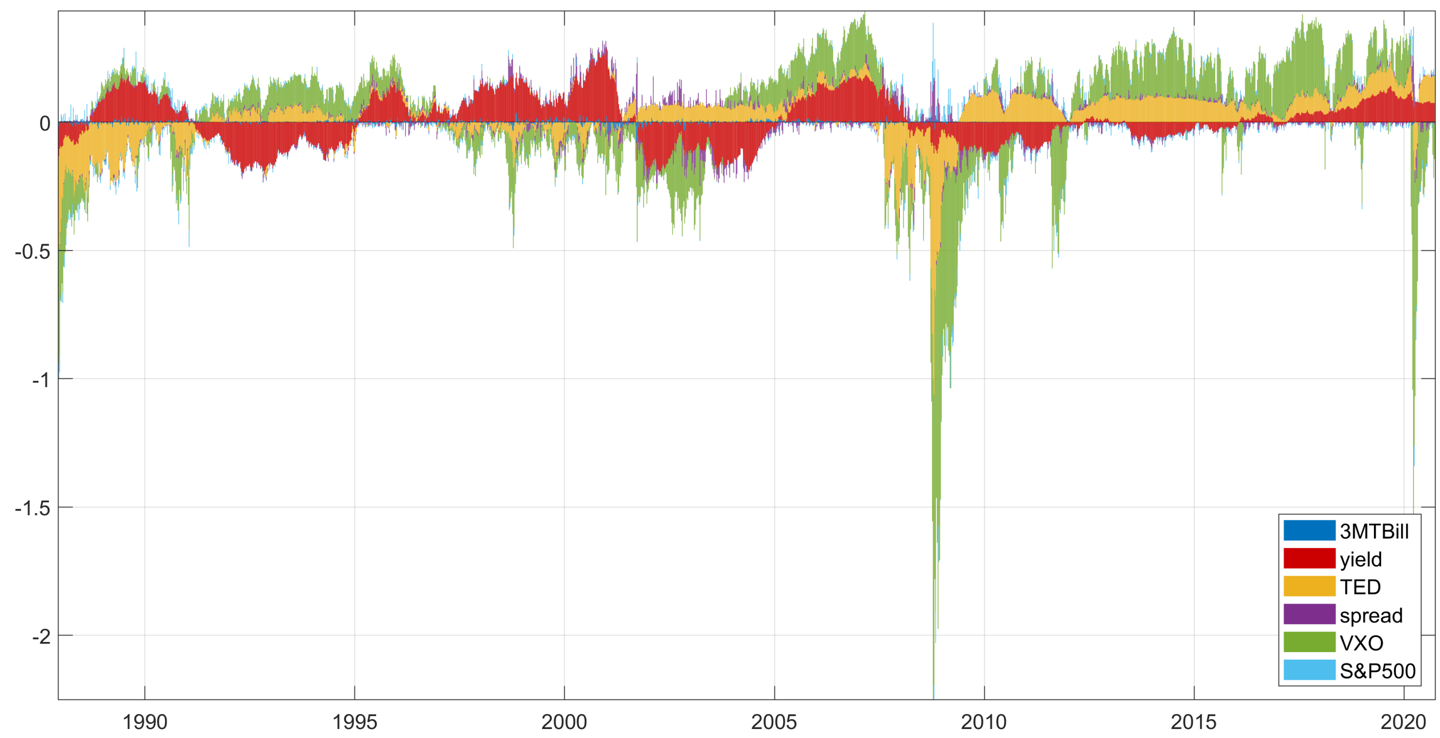


Notes: This figure illustrates the DynamicCoVaR (DCoVaR) from our model. The impact of the different components is given by the DynamicVaR (DVaR, blue line); and the state variables (red line), for the weighted-average of the largest 10 financial institutions. The variables are expressed in units of total 52 week market returns at a weekly frequency (standardized).

For the final analysis in this subsection, we focus on the effect of the state variables. Recall that 6 variables compose the effect of the state variables on the CoVaR: 1 - the change in the three-month yield; 2 - the change in the slope of the yield curve; 3 - short-term TED spread; 4 - change in credit spread; 5 - weekly market return; 6 - equity volatility. Our goal is to evaluate the impact of each of them on systemic risk, so we are able to assess the difference in terms of their relevance/importance. We consider the impact in the case with the time-varying component, that is, in the DynamicCoVaR, for which the results are shown in Figure 1.13.

As we can see, the impact of the state variables seems to be given mostly, by 3 main variables: equity volatility; the change in the slope of the yield curve; and the TED spread. A rise in the equity volatility would be expected to be associated with an increase in systemic risk, since the higher volatility is a reflection of uncertainty and dispersion in equity returns, associated with periods of higher instability and risk in the market, which is consistent with periods of systemic risk. Since the TED spread is a proxy for short-term liquidity risk, it is also conjectured to have a significant influence on systemic risk. For example, one of the most common solutions to address short-term liquidity risk is to sell assets. Recall that this could lead to a fire-sales effect, where the value of similar assets in the balance sheet of this and other institutions would decrease, pointing to the need to sell additional assets, leading to a vicious cycle that affects several financial institutions, making this effect systemic. As for the slope of the yield curve, it reflects the change in the yield according to the maturity associated with the corresponding debt. In addition, it is commonly used as one of the most powerful predictors of future economic growth, inflation, and recessions. As economic growth or recessions are closely related with systemic risk, it seems reasonable that this variable is also relevant for this purpose.

Figure 1.13: State variables components



Notes: This figure illustrates the impact of the state variables on the DynamicCoVaR(DCoVaR). The impact of the different components is given by the change in the three-month yield ('3MTBill', blue line); the change in the slope of the yield curve ('yield',red line), the short-term TED spread ('TED', yellow line), change in credit spread ('spread', purple line), weekly market return ('S&P500', cyan line), and the equity volatility ('VXO', green line), for the weighted-average of the largest 10 financial institutions. The variables are expressed in units of total 52 week market returns at a weekly frequency (standardized).

Finally, the relevance of each variable is different according to the economic/financial conditions. For the case of the yield, it seems to hold greater higher significance of explaining systemic risk in periods of economic expansion, and mild downturns, while the TED spread, and especially equity volatility, seems to hold greater significance of explaining systemic risk in periods of crisis. There also seems to be a high correlation between TED and equity volatility, while the yield seems to counter the effects of the previous 2 state variables in some periods.

1.6.3 Ranking of systemic risk contribution

So far, we have reported on the overall behaviour of systemic risk, and try to isolate the contribution according to each variable in the model. Nonetheless, one important analysis is to evaluate the contribution to systemic risk per financial institution. That is, in this subsection, we seek to evaluate which are the institutions that have a higher contribution to systemic risk. This would be connected to the cross-section component of systemic risk that we explained before, that is, the analysis of the contribution of different financial institutions to systemic risk, in a specific point in time. But how can we properly evaluate this? Given that the contribution to systemic risk changes over time, the ranking changes according to which period we consider. Thus, we will consider the following 3 simple measures: 1 - sum of overall values of losses. Using this measure, the institutions with highest negative values are the ones that could contribute more to systemic risk; 2 – volatility of the series, given by the standard deviation. The higher volatility could be seen as higher procyclicality, and introduce more systemic risk. As a result, the institutions with higher values of standard deviation are the ones that have a higher contribution to systemic risk; 3 – consider focusing on crisis, especially, the 2008 financial crisis. In this case, we focus on an extreme scenario, that is, on periods with extremely high values of losses. The period corresponds to the 2008 financial crisis, and, in the series, constitutes the period with the lowest value. The institutions that get the lower values during this period could be considered to have higher systemic risk.

The results are reported in Table 1.4 in Appendix 1.10.2. We present the results only for the top 10 institutions according to each indicator, that is, the 10 financial institutions that achieved that highest contribution to systemic risk, according to each indicator. We can see that the list changes according to each of the 3 indicators used, and between the standard and the time-varying parameter model. We can, nevertheless, start by focusing on institutions that are within each list. There is no single institution that makes the top 10 list, for all indicators and all models. However, there are institutions that make several lists. For example, Chubb makes the list when using the standard deviation and the crisis indicators, both for the baseline model and the tvp model. Not only that, but we can also see that it is very high in each list (the first one in 2 of the lists, second in a third list, and fourth in the remaining list). Interestingly enough, this is one of the largest insurance companies in the world, but it is not a traditional bank. Huntington Bancshares makes all the 3 lists for the baseline model, but not for the tvp model. It is possible that, since this is closest to the lower bound of our sample, that is, one of the smallest companies in our sample, it could be the main reason for this difference. It could be that the tvp model would give the dimension of the financial institution higher importance, compared with the standard model. Berkshire Hathaway is also present in all the lists, with the exception of the first (sum) indicator. Recall that this is also one of the 10 largest institutions in our sample. There are other institutions that make half of the list (3 out of 6 indicators): Morgan Stanley, Keycorp, Charles Schwab, for example.

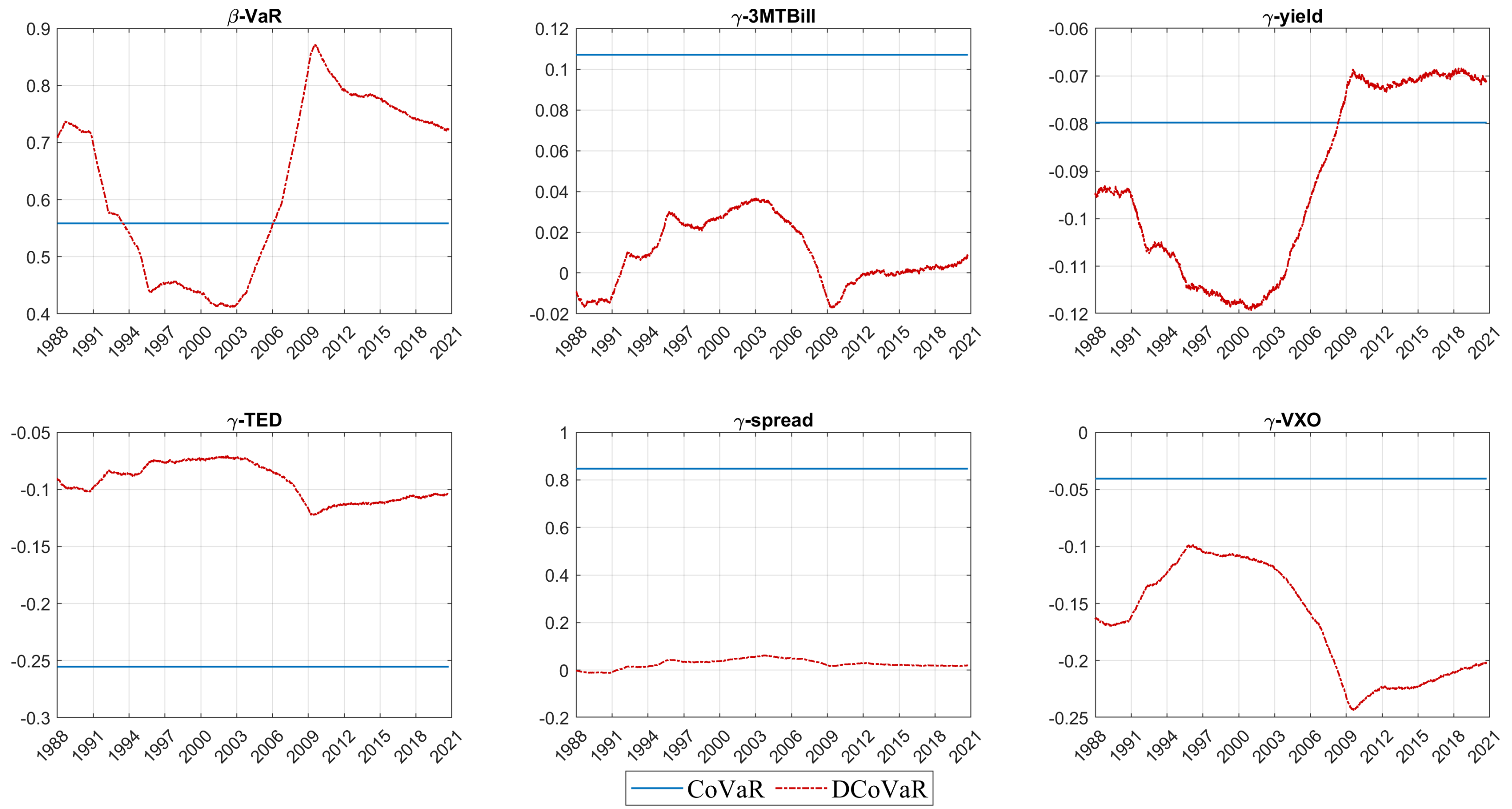
One could argue that size is one of the main determinants of the contribution to systemic risk. And although we will incorporate this variable later on in the model, there is an alternative way for us to consider in the current analysis. Recall that we use the lagged market equity as a weight to calculate the market returns, as an average of the returns of individual institutions in our sample. Thus, we can use the lagged market equity as a proxy for size, and take this into account in the 3 different measures we established before, for both the standard and the tvp model. The results for this alternative scenario are reported in Table 1.5, in Appendix 1.10.2. Notice that, in this case, the list is very similar to the list of the top 10 institutions we provided in the previous section. These results could point in 2 directions: 1 - On one hand, although we attempt to introduce the component of size through the lagged market equity variable, it could be that it unintentionally shifts the analysis to overestimate the importance of size, leading to potential biased results towards larger institutions, despite them not engaging in behaviour which would contribute to systemic risk; 2 - On the other hand, we could also consider that size itself would make these institutions a major source of systemic risk, connected to the Too Big To Fail theory. Hence, the larger institutions would be automatically considered systemic, as any risk affecting them would have an impact on other financial institutions, or on other sectors in the economy. Finally, notice that, even in this scenario, some of the financial institutions outside of the largest top 10 still make the list. That is the case of Chubb and Marsh & Mclennan.

1.6.4 Beta component analysis

In this section, we provide a more detailed analysis of the regressors estimated for each variable, for both the standard CoVaR, and the Dynamic CoVaR. The results can be observed in Figure 1.14. The information shown includes the coefficients for the *VaR*, the *change in the 3-month yield*, the *change in the slope of the yield curve*, the *short term 'TED spread'*, the *change in the credit spread* and the *equity volatility*. Therefore, we are only excluding the estimated coefficients of the *intercept*, and the *weekly market return*, due to their lack of additional contribution to the results obtained. As we explained before, the additional contribution of having a time-varying intercept is to give additional flexibility to the model to adjust to the data. As for the *weekly market return*, the simple fact of being a variable expressed in levels may explain why it does not show more interesting results.

We can see how the time-varying regressors of the Dynamic CoVaR of the different variables change overtime, while the regressors of the CoVaR remain constant. Recall that the regressors give the impact of the different independent variables (the state variables and the idiosyncratic risk) on the dependent variable (systemic risk). While their impact is constant in the original model, we can see how that impact changes over time in our model.

Figure 1.14: Time-series of the betas for the CoVaR and DCoVaR



Notes: The time-series of the regressors for the CoVaR (blue line) and DynamicCoVaR (DCoVaR, red line) is shown for 6 variables: *VaR*, *change in the 3-month yield*, *change in the slope of the yield curve*, *short term 'TED spread'*, *change in the credit spread* and *equity volatility*. The variables are expressed in units of total 52 week market returns at a weekly frequency (standardized).

The more interesting results would be for the case of the *VaR* and the *change in the slope of the yield curve*. Their values rise significantly between 2003 and 2009, which could be seen as an increase in systemic risk over that same period. Not only that, but the fact that their increase begins in 2003 could represent an early warning signal itself to be used in systemic risk measurement. There also seems to be some evidence of a feedback effect, if we focus on the *VaR*. Notice that the β expands significantly between 2003 and 2009, and since it encompasses the influence of idiosyncratic risk (risk of individual institutions) on systemic risk, a larger beta will imply a higher impact of financial distress in a single financial institution on the whole system, which, in turn, leads to an increase of the systemic risk, leading again to an increase of the beta for the *VaR*, feeding a vicious cycle of increase in systemic risk and in the impact of idiosyncratic risk on systemic risk[10]. In other words, the more risk there is already in the system, the higher the additional contribution of risk of each financial institution to the system as a whole.

The γ for the *equity volatility* also reflects remarkable changes between 2003 and 2009, and could also be seen as an early warning signal for systemic risk. Notice that the values of equity volatility will always be positive, and the beta associated with this variable becomes increasingly negative within these years, making the Dynamic CoVaR more negative, increasing systemic risk. This also seems to be the case for the γs of the *change in the 3 month yield* and the *short term 'TED spread'*, although, to a lower extend, since the changes are not as significant. Finally, the γ of the *change in the credit spread* appears to be barely affected throughout the series. Notice that 2 out of the 3 variables with more interesting results that we find here match the main impact of the state variables we found in subsection 1.6.2. This would imply that the large significance of the changes in systemic risk in those 2 state variables are given by changes in the estimated coefficients, and not necessarily due to changes in the state variables themselves.

We provide a more detailed analysis in Table 1.6, in Appendix 1.10.2, for each institution, of the impact of the idiosyncratic risk (VaR) on the systemic risk in each of the models (the original model, CoVaR, and our model, DCoVaR), captured by the estimated coefficient, β. We also provide the market cap, as an indicator of the size of each financial institution in the sample.

If we start the analysis with the β, we can see that the 50% quantile of our DCoVaR seems to be higher in most of the cases, when compared with the β of the CoVaR, implying a higher exposure of the financial system to individual institutions in our model, when compared to the original model. This is also a reflection of our results in the first subplot of Figure 1.14.

In terms of the market cap, financial institutions with higher market capitalization seem to have a higher β, but lower CoVaR and DCoVaR, on average (recall our results for the sum indicator in Table 1.4). This would imply that these institutions yield a higher impact on systemic risk, in case their own institution enters in financial distress, but a lower overall contribution for

[10]Notice that both the CoVaR and VaR are negative values, and more negative values reflect higher risk. As a result, an increase of the β for the VaR will make the CoVaR more negative, increasing systemic risk.

systemic risk. The higher β is expected, as larger financial institutions are expected to have a higher impact on systemic than smaller financial institutions. The lower levels of systemic risk could imply that larger financial institutions are less exposed to macroeconomic frictions. As a result, changes in the state variables would have a lower impact on the individual risk (VaR) of larger institutions, making them more resistance to shocks in the macroeconomy, and contribute less to systemic risk overall. However, we must also consider that the elements provided here are averages, and, therefore, are not considering the procyclical components that we mentioned previously. High levels of the CoVaR and the DCoVaR could simply be a result that larger financial institutions are more procyclical, and since we have more periods of stability in the sample, financial institutions that are more procyclical will have a lower CoVaR and DCoVaR on average.

And although we do not provide an analysis for the overall distribution of the quantiles, we show a clearer picture in Figure 1.24, in Appendix 1.10.2, to confirm our analysis in the previous paragraph. As we can observe, the relationship between the estimated betas and the market capitalization of financial institutions is positive, for the different quantiles. Interestingly enough, it seems that market capitalization as a higher impact on the estimated betas for the 50% quantile, and lower for the other 2 cases, especially for the 75% quantile. This would imply that market capitalization has a higher impact on the relation between individual and systemic risk (the β) for scenarios with moderate risk (for the 50% quantile). For more extreme scenarios, either with higher stability, on one hand, or higher instability, on the other hand, would leave smaller financial institutions more vulnerable, and, thus, increasing the impact of their individual risk on systemic risk. This may be related to them having lower accumulated resources in the event of a crisis, or even in periods of higher stability, having little resources to face even small shocks, or being more vulnerable to low disturbances in or outside the sector. Either way, the main conclusion holds for all scenarios: larger financial institutions have a higher transmission from their individual risk to systemic risk.

1.6.5 Forecasting Systemic risk

In this section, we evaluate the forecasting performance, accuracy and calibration of the quantile regression methods discussed. At each sample point, we predict the CoVaR for a given quantile τ, at a given horizon h. Then, we assess the forecasting properties of each method by defining three evaluation statistics, as established by [Brownlees and Souza, 2021]. The first one is the average empirical coverage, and is defined as:

$$C = \frac{1}{T}\sum_{t=1}^{T} \mathbf{I}_{\{y_t > \mathbb{Q}_\tau(y_t|I_{t-h})\}} \tag{1.21}$$

and measures the accuracy of the quantile forecasts for a given τ. Accurate predictions are expected to have an empirical coverage or 'hit rate' close to the nominal coverage. The second evaluation statistic is the average lengths of the predictions, and can be described as:

$$L = \frac{1}{T}\sum_{t=1}^{T}\hat{Q}_\tau(y_t) - \mathbb{Q}_\tau(y_t|I_{t-h}) \tag{1.22}$$

Where $\hat{Q}_\tau(y_t)$ denotes the (unconditional) τ-th empirical quantile. Quantile forecasts with smaller average lengths are preferred according to this criterion. Finally, we evaluate the quality of our quantile forecasts for different models on the basis of a loss function. The tick loss, which has been found to be a proper loss function to evaluate quantile forecasts by [Giacomini and Komunjer, 2005], can be defined as:

$$TL = \frac{1}{T}\sum_{t=1}^{T}\rho_\tau(y_t - \mathbb{Q}_\tau(y_t|I_{t-h})) \tag{1.23}$$

Models delivering statistically significantly lower tick loss statistics are preferred. We evaluate the significance of the gains to forecasting in terms of tick loss by using Diebold-Mariano tests following [Brownlees and Souza, 2021].

Table 1.8 in Appendix 1.10.2 provides a summary of the forecasting performance of the model considered throughout the paper (given by the QR(TVP)) and compares it to the baseline quantile regression model of [Adrian and Brunnermeier, 2016] which does not include the time varying component (given by the QR(baseline)). If the predictive capability of one model is better than the other, then one would expect to see a consistent outperformance, given by the different indicators listed above. As we described before, for each different model, the three statistics - average empirical coverage, average lengths and tick loss, are computed for a given quantile τ and forecast horizon h.

The main conclusion we can take is that there is not an outperformance of one of the models over the other, in terms of forecasting. The average lengths (L) clearly favours our model over the standard one, since the values are always lower, for any given scenario. However, the average empirical coverage (C) seems to mostly favour the standard model, while the tick loss (TL) seems to give conflicting results. For example, in the 12-week forecasting horizon (h=12) scenario, most of the results from the tick loss (TL) favour our model (except when $\tau = 0.1$), while the opposite happens when we consider the 4-week forecasting horizon (h=4) scenario. As for the average empirical coverage (C), notice that in the 12-week forecasting horizon (h=12) scenario, for $\tau = 0.01$, our model is closest to the 0.99 nominal coverage (more specifically, this would be 0.0028 in our model vs 0.0061 in the standard model), and this is also the case for $\tau = 0.025$, since our model is also closest to the 0.975 nominal coverage. But if we observe the remaining scenarios, the average empirical coverage (C) favours the baseline model. Lastly, notice that the Diebold-Mariano tests only find one of the tick loss values to be statistically significant, at 5% (for h=12 and τ = 0.05), casting further doubt on the choice of a specific model in terms of forecasting.

To a certain degree, there could be valid reasons for the outperformance of the standard model over our model, in some of the forecasting indicators. Traditionally, more parsimonious models are able to achieve better forecasting results, which could be one of the potential reasons for our conflicting conclusions between the different indicators (when discussing a parsimony characteristic in terms of forecasting, we mean in terms of lack of overfitting, and, usually, smaller forecasted confidence intervals). Parsimonious models tend to make more accurate predictions on new datasets, because they are less likely to overfit the original dataset. We also do not consider this as an impediment of our results in the previous subsection, since the main goal of adding the time-varying parameter component to our model is to be used as a measurement of systemic risk, and not as a forecast measure.

On the other hand, the scenarios provided in the previous table are focused on the short-run. As a result, we provide additional scenarios for the medium (between 15 and 25 weeks) and long-term (between 30 and 40 weeks), which can be seen in Table 1.9 and Table 1.10, respectively, in Appendix 1.10.2. From the analysis of the 2 tables, we can see that the results are starkly different from the previous ones. While before, the different indicators pointed to different models, all the indicators now clearly favor our model, with no exception. This implies that our model outperforms the standard model, in terms of forecasting. Also, the Diebold-Mariano statistics are statistically significant for $\tau = 0.05$ and $\tau = 0.1$, almost all at 1%, with only one at 5% significance level. In some cases, the Diebold-Mariano statistics are significant even for $\tau = 0.025$, but none are significant at $\tau = 0.01$.

Given the new information, we can take the following conclusions: 1 - the accuracy of our model, in terms of forecasting, increases with h, the horizon in number of weeks, given by the information of the 3 different indicators between Tables 1.8, 1.9 and 1.10; 2 - the forecasting accuracy of our model also increases with τ, given by the Diebold-Mariano statistics. This seems to imply that focusing only on very extreme scenarios (the lowest 1% of the returns in the sample) could decrease the reliability of the forecasting results, and should possibly consider instead focusing on the lowest 5%. While the quantile regressions are preferable in the case of fat tails, it could also be the case that only considering a small subsample (for example, the 1% case) would lead to very few elements being taken into account for the estimation, decreasing the reliability of the estimated results; 3 - for the short-term (until 12 weeks), there is no forecasting outperformance of one of the models over the other; 4 - for the medium and long term, the three indicators clearly reflect that our model possesses a higher forecasting ability than the standard model. These results are even strengthened by the Diebold-Mariano statistics for $\tau \geq 5\%$, and even in some cases for $\tau = 2.5\%$.

1.7 CoVaR and Financial Sector Data

In the last section, we discussed the results for the analysis of the model, only considering the state variables, reflecting changes in the macroeconomic conditions, and the returns of each institution. Thus, we interpreted the differences in our results from potential additional vulnerabilities, either from sources other than the macroeconomic conditions, or relating to the relationship of the exposure to macroeconomic frictions being dynamic. However, it is also possible that these differences result from the different choices made by the individual financial institutions, and that these choices are not captured by the corresponding returns. These different choices can be described more clearly by balance sheet data. Given similar macroeconomic conditions, different options regarding leverage, for example, can lead some financial institutions to be more exposed, or more robust, compared to others. It ensues that, by incorporating these additional variables, we will be able to improve the measurement accuracy of the indicator. Not only that, the analysis of balance sheet data, which is idiosyncratic between each institution, are likely to give us more detail on the differences between each financial institution's contribution to systemic risk (recall that, in the standard model, the only component of idiosyncratic data were the market returns, all the state variables were similar to each financial institution).

The procyclicality component that we identified in the previous section would point to additional changes in our model, in terms of the periods of our variables, compared to our systemic risk indicator. With the 'volatility paradox' (as we described in the literature review, [Brunnermeier and Sannikov, 2014] established the term 'volatility paradox", to refer to the periods of low volatility, that lead financial institutions to underestimate systemic risk and take actions accordingly), regulations that are established on contemporaneous indicators would underestimate risk when volatility is low (when the build-up of systemic risk takes place), and overestimate risk when volatility is high (in these periods, the excessive accumulation of risk already took place in previous periods, and only the consequences of the excessive risk taking are reflected). We can see this in Figure 1.9, for example. Although we can observe that our measure anticipates the actual market equity losses in the 2008 financial crisis (notice that the losses manifest around 2010, while the significant decrease of the DCoVaR takes place around 2007-2008), we could also argue that the risk-taking behaviour took place prior to the large decline shown by the DCoVaR. Thus, regulations that would not take into account this procyclicality aspect would not sufficiently dampen the risk taking in periods of expansion, and would be too restrictive in periods of crisis, potentially exacerbating the negative effects (for example, through fire-sales effects).

Finally, we change the frequency from weekly to quarterly data, due to data availability for our balance sheet data component.

1.7.1 Model changes - contemporaneous

Thus, in accordance with [Adrian and Brunnermeier, 2016], we introduce the following changes in the model to transform the DynamicCoVaR to incorporate additional sources of risk, in the form of balance sheet data. We will incorporate these 2 components separately. The initial step is to re-estimate the regression coefficients of the model, but simply adding the balance sheet data. More specifically, for the original mode of [Adrian and Brunnermeier, 2016], this would correspond to:

$$X_t^i = \alpha_q^i + \gamma_q^i M_{t-1} + \theta_q^i B_{t-1}^i + \varepsilon_{q,t}^i, \tag{1.24}$$

$$X_t^{\mathbb{S}|i} = \alpha_q^{\mathbb{S}|i} + \gamma_q^{\mathbb{S}|i} M_{t-1} + \theta_q^{\mathbb{S}|i} B_{t-1}^i + \beta_q^{\mathbb{S}|i} X_t^i + \varepsilon_{q,t}^{\mathbb{S}|i}. \tag{1.25}$$

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} + \hat{\theta}_q^i B_{t-1}^i, \tag{1.26}$$

$$CoVaR_{q,t}^{\mathbb{S}|i} = \hat{\alpha}_q^{\mathbb{S}|i} + \hat{\gamma}_q^{\mathbb{S}|i} M_{t-1} + \hat{\theta}_q^{\mathbb{S}|i} B_{t-1}^i + \hat{\beta}_q^{\mathbb{S}|i} VaR_{q,t}^i. \tag{1.27}$$

Notice that the only difference from the original model is to add the balance sheet data (institution characteristics and additional institution characteristics) into the estimation, which is comprised by the B_{t-1}^i. Consider that this supplementary data, unlike the state variables, will be different for each institution in the sample, in addition to the differences in each period. When we consider the same changes in our DynamicCoVaR model:

$$X_t^i = \alpha_{q,t}^i + \gamma_{q,t}^i M_{t-1} + \theta_{q,t}^i B_{t-1}^i + \varepsilon_{q,t}^i, \tag{1.28}$$

$$X_t^{\mathbb{S}|i} = \alpha_{q,t}^{\mathbb{S}|i} + \gamma_{q,t}^{\mathbb{S}|i} M_{t-1} + \theta_{q,t}^{\mathbb{S}|i} B_{t-1}^i + \beta_{q,t}^{\mathbb{S}|i} X_t^i + \varepsilon_{q,t}^{\mathbb{S}|i}. \tag{1.29}$$

$$DVaR_{q,t}^i = \hat{\alpha}_{q,t}^i + \hat{\gamma}_{q,t}^i M_{t-1} + +\hat{\theta}_{q,t}^i B_{t-1}^i, \tag{1.30}$$

$$DCoVaR_{q,t}^{\mathbb{S}|i} = \hat{\alpha}_{q,t}^{\mathbb{S}|i} + \hat{\gamma}_{q,t}^{\mathbb{S}|i} M_{t-1} + \hat{\theta}_{q,t}^{\mathbb{S}|i} B_{t-1}^i + \hat{\beta}_{q,t}^{\mathbb{S}|i} DVaR_{q,t}^i. \tag{1.31}$$

1.7.2 Model changes - dynamic

In this second scenario, we incorporate the second component, taking the estimation of the CoVaR and the DCoVaR on *lagged* state variables and *lagged* institutions characteristics. The lagged periods are defined by the h variable, and are constructed for number of quarters. Again, in the original [Adrian and Brunnermeier, 2016] model, this would lead to:

$$X_t^i = \alpha_q^i + \gamma_q^i M_{t-1-h} + \theta_q^i B_{t-1-h}^i + \varepsilon_{q,t}^i, \tag{1.32}$$

$$X_t^{\mathbb{S}|i} = \alpha_q^{\mathbb{S}|i} + \gamma_q^{\mathbb{S}|i} M_{t-1-h} + \theta_q^{\mathbb{S}|i} B_{t-1-h}^i + \beta_q^{\mathbb{S}|i} X_t^i + \varepsilon_{q,t}^{\mathbb{S}|i}. \tag{1.33}$$

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1-h} + \hat{\theta}_q^i B_{t-1-h}^i, \tag{1.34}$$

$$CoVaR_{q,t}^{\mathbb{S}|i} = \hat{\alpha}_q^{\mathbb{S}|i} + \hat{\gamma}_q^{\mathbb{S}|i} M_{t-1-h} + \hat{\theta}_q^{\mathbb{S}|i} B_{t-1-h}^i + \hat{\beta}_q^{\mathbb{S}|i} VaR_{q,t}^i. \tag{1.35}$$

While for the model with time-varying parameters, this would lead to:

$$X_t^i = \alpha_{q,t}^i + \gamma_{q,t}^i M_{t-1-h} + \theta_{q,t}^i B_{t-1-h}^i + \varepsilon_{q,t}^i, \tag{1.36}$$

$$X_t^{\mathbb{S}|i} = \alpha_{q,t}^{\mathbb{S}|i} + \gamma_{q,t}^{\mathbb{S}|i} M_{t-1-h} + \theta_{q,t}^{\mathbb{S}|i} B_{t-1-h}^i + \beta_{q,t}^{\mathbb{S}|i} X_t^i + \varepsilon_{q,t}^{\mathbb{S}|i}. \tag{1.37}$$

$$DVaR_{q,t}^i = \hat{\alpha}_{q,t}^i + \hat{\gamma}_{q,t}^i M_{t-1-h} + + \hat{\theta}_{q,t}^i B_{t-1-h}^i, \tag{1.38}$$

$$DCoVaR_{q,t}^{\mathbb{S}|i} = \hat{\alpha}_{q,t}^{\mathbb{S}|i} + \hat{\gamma}_{q,t}^{\mathbb{S}|i} M_{t-1-h} + \hat{\theta}_{q,t}^{\mathbb{S}|i} B_{t-1-h}^i + \hat{\beta}_{q,t}^{\mathbb{S}|i} DVaR_{q,t}^i. \tag{1.39}$$

1.7.3 Balance sheet data - Institution characteristics

In this section, we describe the variables considered for the institution characteristics. All the additional information was obtained from the WRDS (Wharton Research Data Services):

1. Leverage. In order to obtain these estimations, we use the ratio of market value of assets to market equity. The market value of assets is obtained from the "Total Fair Value of Assets (TFVAQ)".

2. Maturity Mismatch. This is defined as the ratio of book assets to short term debt, less short term investments, less cash. The book value of assets is defined as "book value of assets (ATQ)", for short term debt we use debt in current liabilities (DLCQ), and for the short term investments and cash we resort to the variable "cash and short-term investments (CHEQ)". Similar to [Adrian and Brunnermeier, 2016], we have constrained the observations of the maturity mismatch, with a truncation between 10% and 90%.[11]

[11] This is relatively similar to what the authors did in the original article (but the interval of constraint is only between 1% and 99%). However, we need to impose this constraint in order for the moments (mean and standard deviation) to match the ones in the original article. This seems to be the preferable approach, since we still remain with approximately 68% of the observations. The alternative, using the TFVAQ variable, would also be close to the moments in the original article, and we would only need to restrict the sample to the same interval of 1% and

3. Size. This is calculated as the log of total market equity for each firm, divided by the log of the cross sectional average of market equity. The basis for this information is already laid out in the original model.

4. Boom indicator. This indicator gives (for each firm) the number of consecutive quarters of being in the top decile of the market-to-book ratio across firms, and can be calculated with the variables obtained in the previous points.

Table 1.2 in Appendix 1.10.2 describes a summary for the statistics of these 4 variables.

1.7.4 Balance sheet data - Additional Institution characteristics

In addition to the previous variables, we also consider additional characteristics, which are available only for a subsample of bank holding companies. On the asset side, we consider: 1 - loans (given by the variable "loans net of unearned income loans, gross (LCQ)"); 2 - loan loss allowances (given by the variable "total allowance for loan loss (RCLQ)"); 3 - intangible loan allowances (given by the variable "allowance/reserves for other losses (AROLQ)"); 4 - intangible assets (given by the variable "intangible assets (INTANQ)"); 5 - trading assets (given by the combination of the variables "assets held for sale (AHSQ)" and "other assets held for sale (OAHSQ)"). As for the liability side, we include: 6 - interest bearing deposits (DIBQ); 7 - non-interest-bearing deposits (given by the variable "total savings deposits (DPSCQ)"); 8 - large time deposits (given by the variable "total time deposits, other than savings (DPTICQ)"); 9 - total demand deposits (DPDCQ). All these variables are expressed as a % of total assets.

99%, but we would have a lower number of observations (around 31.7%). As a result, we have opted for the first possibility. In the original article, some additional constraints were incorporated, for example, removing leverage and book-to-market ratios less than 0 and greater than 100. We, on the other hand, have not applied these constraints in our data.

1.8 Additional results

1.8.1 Contemporaneous analysis

In this subsection, we present the results when we include the balance sheet data (institution and additional institution characteristics) into the model, as described in subsection 1.7.1. We begin with the contemporaneous analysis, that is, for the same period, and then follow with the scenario with the lagged state variables and institution characteristics. The following 3 figures show the results for quarterly frequency: 1 - the CoVaR and the DynamicCoVaR (DCoVaR) with quarterly frequency, for the previous standard scenario, in Figure 1.15; 2 - the CoVaR and the DynamicCoVaR (DCoVaR) with quarterly frequency, where we include the institution characteristics and additional institution characteristics, but just for the CoVaR, in Figure 1.16; 3 - the CoVaR and the DynamicCoVaR (DCoVaR) with quarterly frequency, where we include the institution characteristics and additional institution characteristics, both for the VaR and for the CoVaR, in Figure 1.17. We choose to provide these 3 different scenarios, not only to evaluate the effects of including the institution characteristics in our estimations, but also to separate the potential different reasons for those differences.

We begin with Figure 1.15. As we can see, the behaviour of the series is very similar to the results that we obtained previously (with DCoVaR achieving a higher volatility and procyclicality than in the standard model). The only difference is that the series now seems to be smoother, obviously, due to the simple change in the frequency, from weekly to quarterly. If we, then, go to Figure 1.16, we are able to see the impact of the institutions' characteristics, but only isolating for their direct impact on the CoVaR (in this case, the VaR does not consider the balance sheet data). We can see that this leads to an overall decrease of the estimated DynamicCoVaR, compared with the standard measure. It seems that, unlike before, where there was an increase of the DynamicCoVaR in periods of higher returns, now, even in those cases, the DynamicCoVaR seems to have decreased. The institution characteristics seem to, therefore, lead to more overall conservative estimates of the systemic risk, instead of higher volatility and procyclicality. Finally, when we analyze Figure 1.17, where we also incorporate the additional balance sheet information on the estimations of the VaR, we can see additional differences in the series.

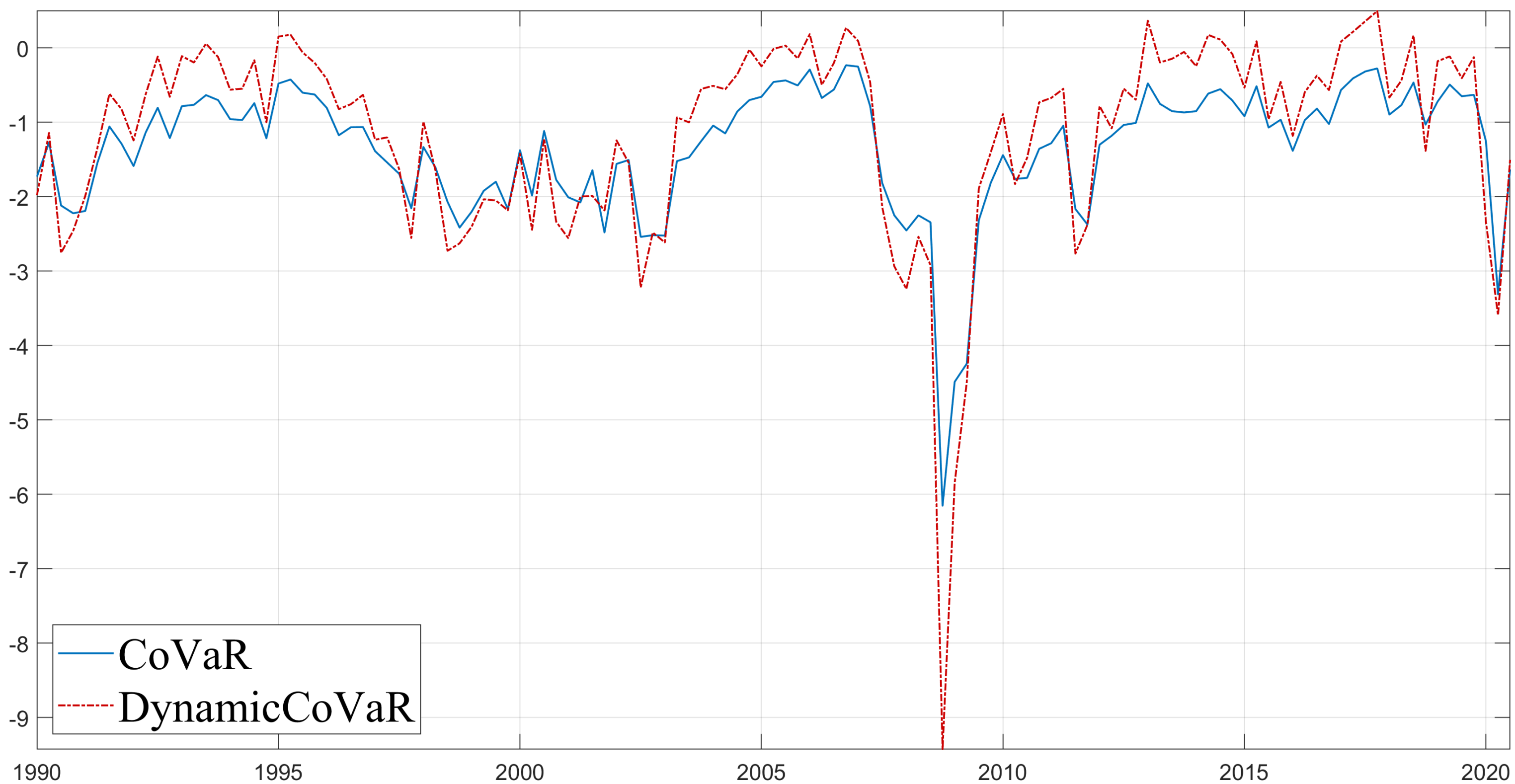
As a result, we are able to take 2 additional conclusions from the comparison of the last 2 Figures: 1 - Unlike before, where the estimations of the idiosyncratic risk were not impacted by the time-varying parameter component (since the VaR and the DVaR in Figure 1.22 are exceedingly similar), the inclusion of the balance sheet data now results in the time-varying parameter component exerting a difference in idiosyncratic risk. Notice that we are able to conclude this from the differences between Figures 1.16 and 1.17. If the new VaR and DVaR were similar, like in the standard scenario, there would be no difference between Figures 1.16 and 1.17.

We could argue, however, that the differences could result from the change of the impact of the individual risk of each institution in the systemic risk over time (the $\hat{\beta}_{q,t}^{\mathbb{S}|i}$ component), and not necessarily from the changes in the DVaR. But notice that Figure 1.16 already takes that into account. Even if the estimations of the DVaR are the same, the model in Figure 1.16 still incorporates the change of the impact of the individual risk of each institution in the systemic risk over time (the $\hat{\beta}_{q,t}^{\mathbb{S}|i}$ component). Thus, the only possible explanation for the difference in the two Figures is that the impact on the DynamicVaR from the incorporation of the institution characteristics (captured by the DCoVaR) are very different from the impact on the VaR from the incorporation of the institution characteristics (captured by the CoVaR). One possible explanation for this difference is the fact that, before, most of the independent variables consisted of state variables (with the exception of the returns), which are equivalent for each individual institution.

On the other hand, the institution characteristics are specific for each financial institution, which could also be a possible explanation that it could lead to differences in the idiosyncratic component estimated, unlike before. That is, the new idiosyncratic variables included in the model seem to exert a difference in the estimation of the idiosyncratic risk (given by the differences between VaR and DVaR now), when we add the time-varying component into the model; 2 - there also seems to be additional volatility in the series, when we look into the final scenario of Figure 1.17, but it doesn't necessarily seems to be procyclical. For example, there are cases where the DynamicCoVaR is above the CoVaR, (around 2000), and periods when they are very close (for example, around 2015), but the cases are very few. In most cases, the differences between the DynamicCoVaR and CoVaR are even more prominent in the last case, compared to Figure 1.16.

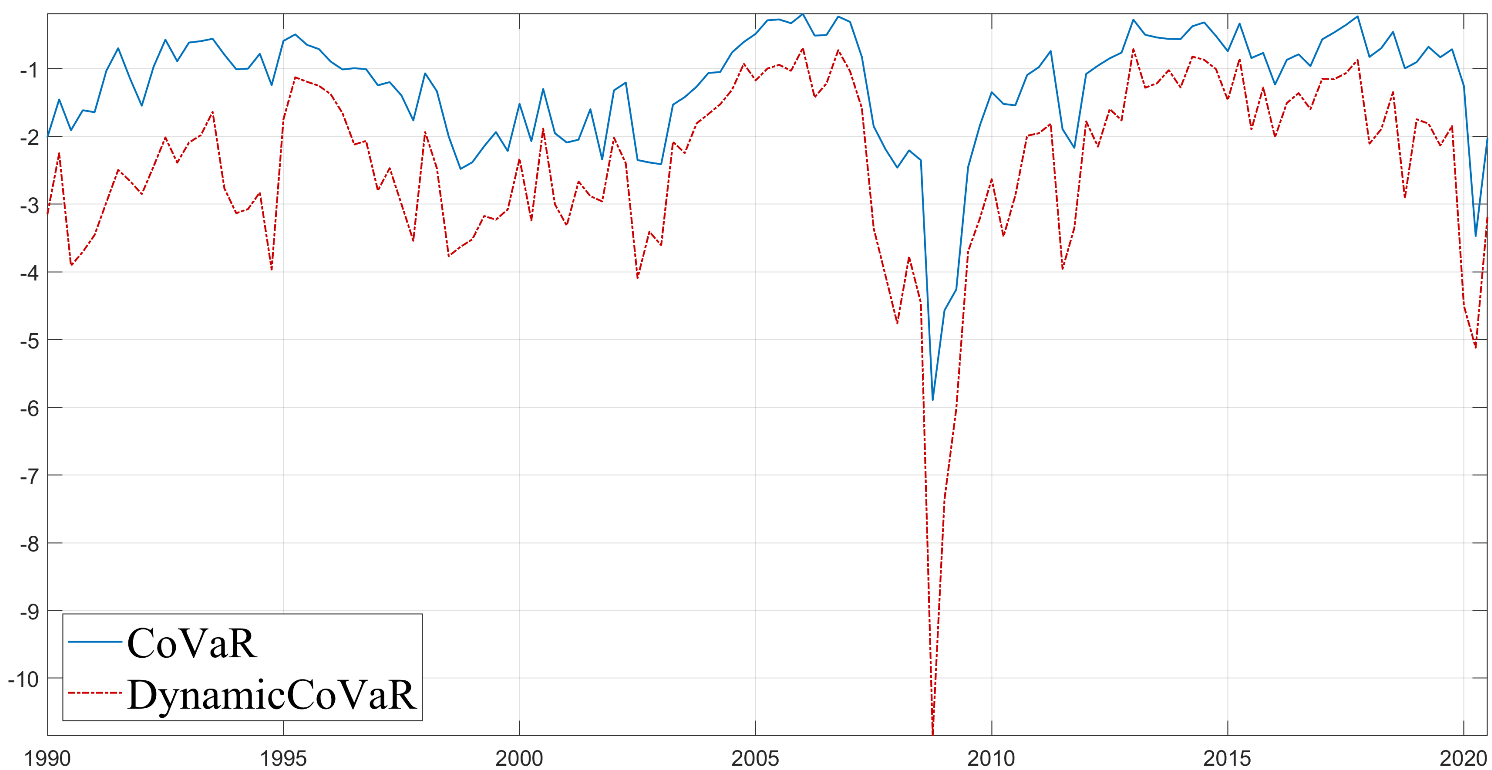
One possible explanation for this result is the conflicting effect that balance sheet data can have on idiosyncratic vs systemic risk. An obvious example is the case of fire sales. In the case of financial distress, some financial institutions may resort to selling some of their assets in order to garner additional resources (cash in our model, for example). This will obviously decrease their idiosyncratic risk. However, selling their assets will have an adverse impact on the value of similar assets held by other financial institutions, decreasing the value of these assets in their balance sheet, or even in the balance sheet of the financial institution in question, if they still hold similar assets (in our model, this could exert an adverse effect, either through the leverage, by decreasing the value of the assets, or a drop in the trading assets). The adverse effect of the asset sale on the value of assets held by other institutions will be the increase in systemic risk component in this example. Another example could be a simultaneous fall of the market capitalization (at least, in comparison to other financial institutions) and rise of the level of debt. On one hand, the increase in the amount of debt is likely to increment its individual/idiosyncratic risk, and have an impact on the systemic risk (CoVaR) through the idiosyncratic risk (VaR). But on the other hand, the decrease in the market capitalization compared with the other financial institutions will lead to a lowering of the importance and relevance of the specific financial institution for the market, and, therefore, decrease its impact on systemic risk.

Figure 1.15: CoVaR Functions - quarterly



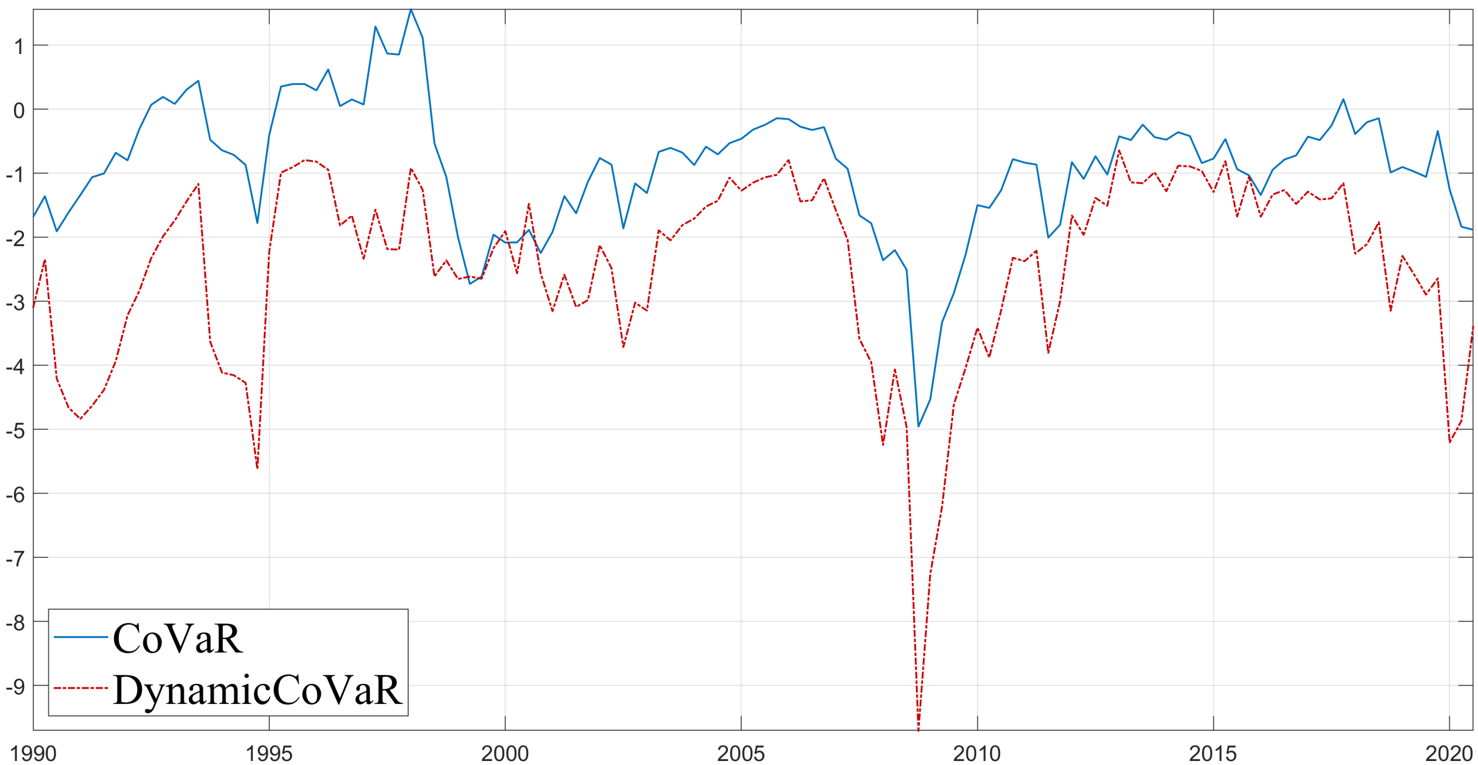
Notes: The CoVaR refers to the model of [Adrian and Brunnermeier, 2016] (blue line); while the DCoVaR refers to the Dynamic CoVaR proposed in the body of the paper (red-dashed line), for the weighted-average of the largest 10 financial institutions. The variables are expressed in units of total 4 quarter market returns at a quarterly frequency (standardized).

Figure 1.16: CoVaR Functions - balance sheet data



Notes: The CoVaR refers to the model of [Adrian and Brunnermeier, 2016] (blue line); while the DCoVaR refers to the Dynamic CoVaR proposed in the body of the paper (red-dashed line), with the direct effect of institution characteristics on the CoVaR and DCoVaR, for the weighted-average of the largest 10 financial institutions. The variables are expressed in units of total 4 quarter market returns at a quarterly frequency (standardized).

Figure 1.17: CoVaR Functions - balance sheet+VaR data



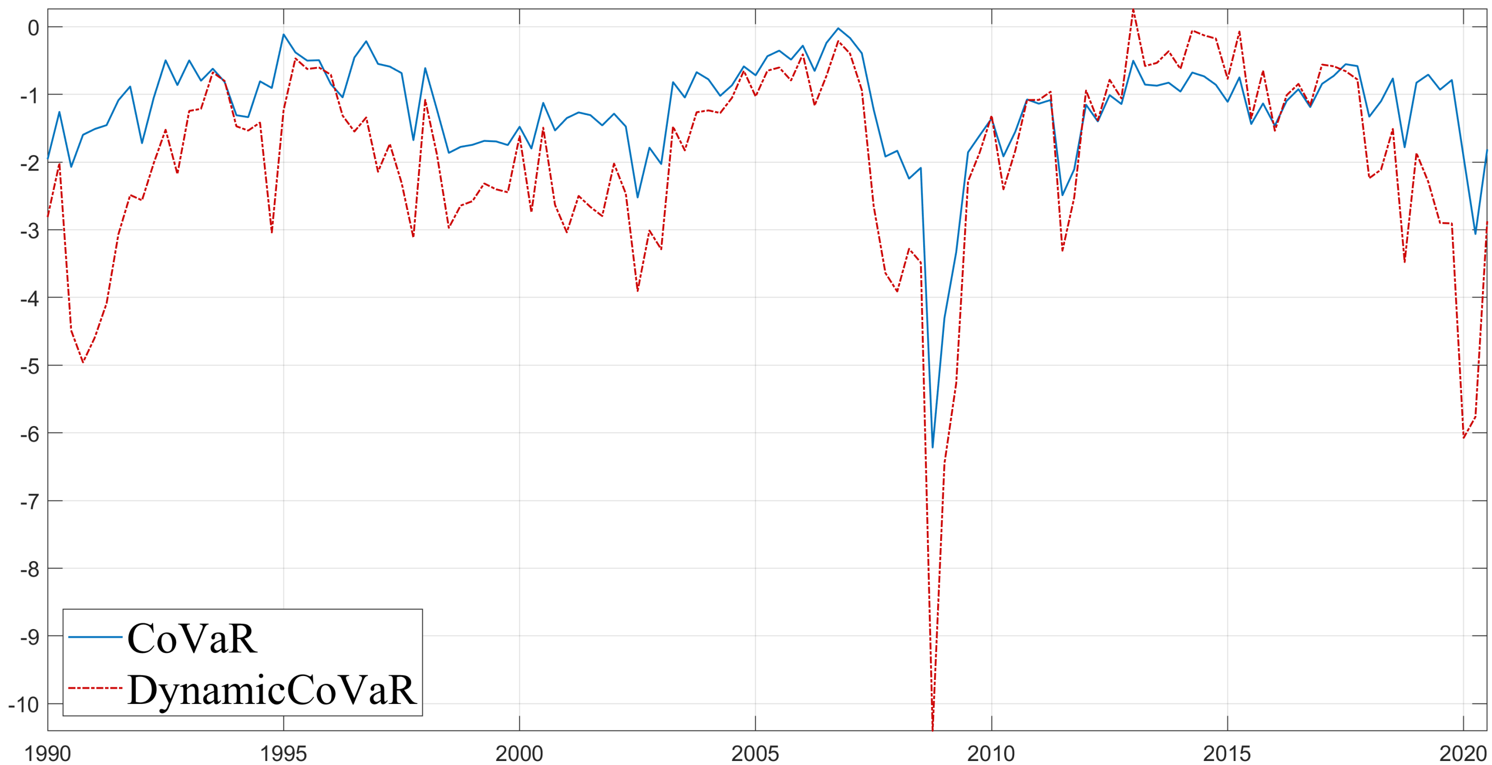
Notes: The CoVaR refers to the model of [Adrian and Brunnermeier, 2016] (blue line); while the DCoVaR refers to the Dynamic CoVaR proposed in the body of the paper (red-dashed line), with the direct and indirect (through the VaR and DVaR) effect of institution characteristics on the CoVaR and DCoVaR, for the weighted-average of the largest 10 financial institutions. The variables are expressed in units of total 4 quarter market returns at a quarterly frequency (standardized).

Before proceeding to the dynamic analysis (with lagged state variables and balance sheet data), we should discuss some concerns regarding the previous results. Particularly, we want to be certain that the differences from the 2 series do not stem from outliers in one or more variables from the additional data[12]. We started with an analysis of the outliers in the sample, which we defined using the Inter-Quartile Range (IQR): 1 - calculate the 1^{st} quartile (Q1, or 25^{th} percentile), and 3^{rd} quartile (Q3, or 75^{th} percentile); 2 - calculate the Inter-Quartile Range (IQR), which is simply the difference between the 2 previous quartiles; 3 - calculate the lower and higher range limit, which is simply equal to Q1 – 1.5*x*IQR and Q3 + 1.5*x*IQR, respectively. The outliers are, thus, defined as elements within the data with more than 1.5 times the length of the inter-quartile range away from either the lower or upper quartiles, that is, with values either above the higher range limit or below the lower range limit. From this assessment, however, we identified relatively few outliers (in comparison with overall observations), and also relatively close to the upper and lower range limits (by comparing with the minimum and maximum values for each variable). Just in case, we proceeded with either the removal of the outliers from our sample, or testing the model without variables with outliers. However, the estimated results did not seem to differ significantly.

Finally, we provide a scenario analysis with just the 4 main institution characteristics: Leverage; Maturity Mismatch; Size; and Boom. The results are presented in Figure 1.18. If we compare with Figure 1.15, we can see that there is still some procyclicality that remains (more towards the end of the series), but we can also see the main change is the overall decrease of the values of the DynamicCoVaR compared with the CoVaR. This is similar to the result in 1.17, although the difference is not as pronounced as before. This result supports our previous conclusion that, indeed, the change in the series is due to the introduction of institution characteristics. It seems that, the more institution characteristics we include in the estimation, the more conservative/negative the estimations of the DynamicCoVaR compared to the CoVaR, and the higher the difference between the 2 series.

[12]There could also be some concerns regarding the priors established. However, no changes were made to the priors between the current and the standard scenario. As a result, we can eliminate that as a possible explanation.

Figure 1.18: CoVaR Functions - balance sheet (just main 4)+VaR data



Notes: The CoVaR refers to the model of [Adrian and Brunnermeier, 2016] (blue line); while the DCoVaR refers to the Dynamic CoVaR proposed in the body of the paper (red-dashed line), with the direct and indirect (through the VaR and DVaR) effect of the 4 main institution characteristics on the CoVaR and DCoVaR, for the weighted-average of the largest 10 financial institutions. The variables are expressed in units of total 4 quarter market returns at a quarterly frequency (standardized).

We should also establish a comparison between the DynamicCoVaR before and after the introduction of balance sheet data. We can do this by simply looking to the values of Figures 1.15 and 1.17, and we easily understand that the estimations with balance sheet data are more pessimistic/negative than the standard scenario. Before and after the 2008 financial crisis, the values of the DynamicCoVaR in the standard scenario are between 0 and -3, while they are between -1 and -5 for the DynamicCoVaR with the balance sheet data. So it again seems to support that the inclusion of the institution characteristics lead to more pessimistic estimates of the DCoVaR, and perhaps a small increase in the volatility.

1.8.2 Dynamic analysis

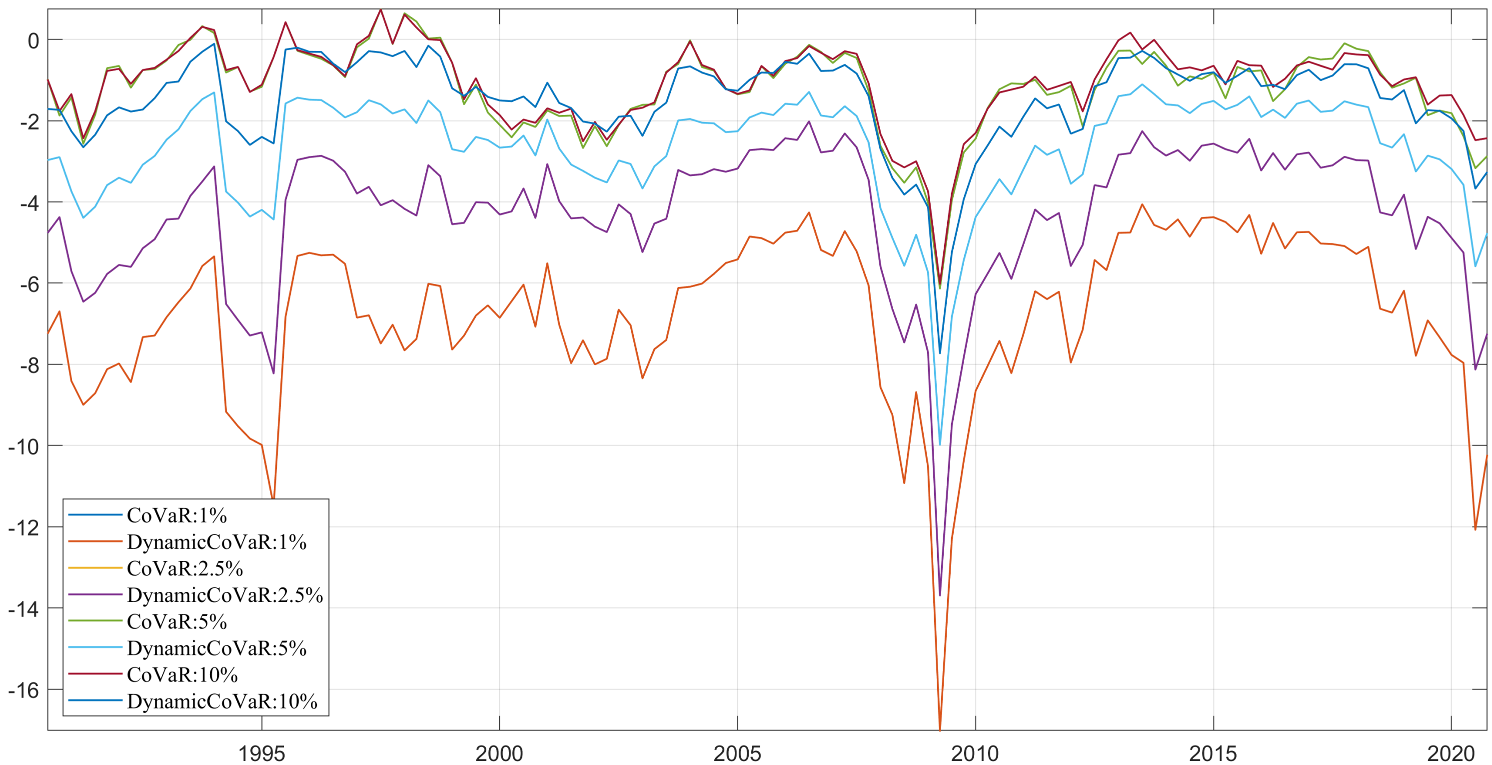
We now turn to the analysis for the model in subsection 1.7.2. We start with Figure 1.19, where we have the calculations for the CoVaR and DCoVaR with h = 1, that is, state variables and balance sheet data lagged for 1 quarter. We also provide additional scenarios, for different quantiles, τ. The different quantiles considered here are the same as in the forecasting scenario, that is, for $\tau = 0.01$, 0.025, 0.05 and 0.1. Recall that the considerations for different quantiles are connected with the definition of what we consider an extreme scenario. When $\tau = 0.01$, the focus is on very extreme cases of low returns, that is, the lowest 1% of returns, which would usually comprise of periods of crises (although it is possible that individual institutions have very low returns outside of periods of crises, it is likely that most low returns of most institutions will be concentrated within or around these periods). When $\tau = 0.1$, we would also be considering the lowest returns between 1% and 10%, which is likely to also consist of mild downturns. It is also important to point out that the h is defined in comparison with the standard and contemporaneous scenario. Notice that, in these cases, we are already lagging the state variables, institution characteristics and additional institution characteristics by one period. As a result, when we define the scenario for lag of 1 quarter (h = 1), for example, it will correspond to a lag of 1 period compared to the standard and contemporaneous model, and a total lag order of 2 periods.

Notice that the standard scenario, with $\tau = 0.05$, is very similar to the contemporaneous case, in Figure 1.17. Also, the changes in τ seem to exert very little effect on the standard CoVaR estimations. In fact, the different estimations are even indistinguishable for lower levels of τ, and we can only distinguish between the scenarios for $\tau = 5\%$ and 10%, with relatively little different between them. On the other hand, the estimations of the DCoVaR are extremely sensitive to the values of τ. In fact, there seems to be almost a parallel shift downwards, with the increase in the values of τ. It seems that the tvp model interprets the more extreme scenarios, given by lower values of τ, as more pessimistic estimates of systemic risk.

We follow-up with Figure 1.20, which reflects the estimations of the CoVaR and DCoVaR, when the lag order is increased to 4 quarters (h = 4). At first sight, there does not seem to be a notable difference when we compare with the $\tau = 5\%$ scenario in Figure 1.19. However, it could be preferable to compare with the scenario for the contemporaneous case (h = 0), in Figure 1.17. It seems that the lagging component has reduced the volatility of the DCoVaR measure, with the exception of the largest decline in the 2008 financial crisis, for which the value is maintained. In the case of the CoVaR, there is no change in the volatility, but there is a large decrease in the 2008 financial crisis.

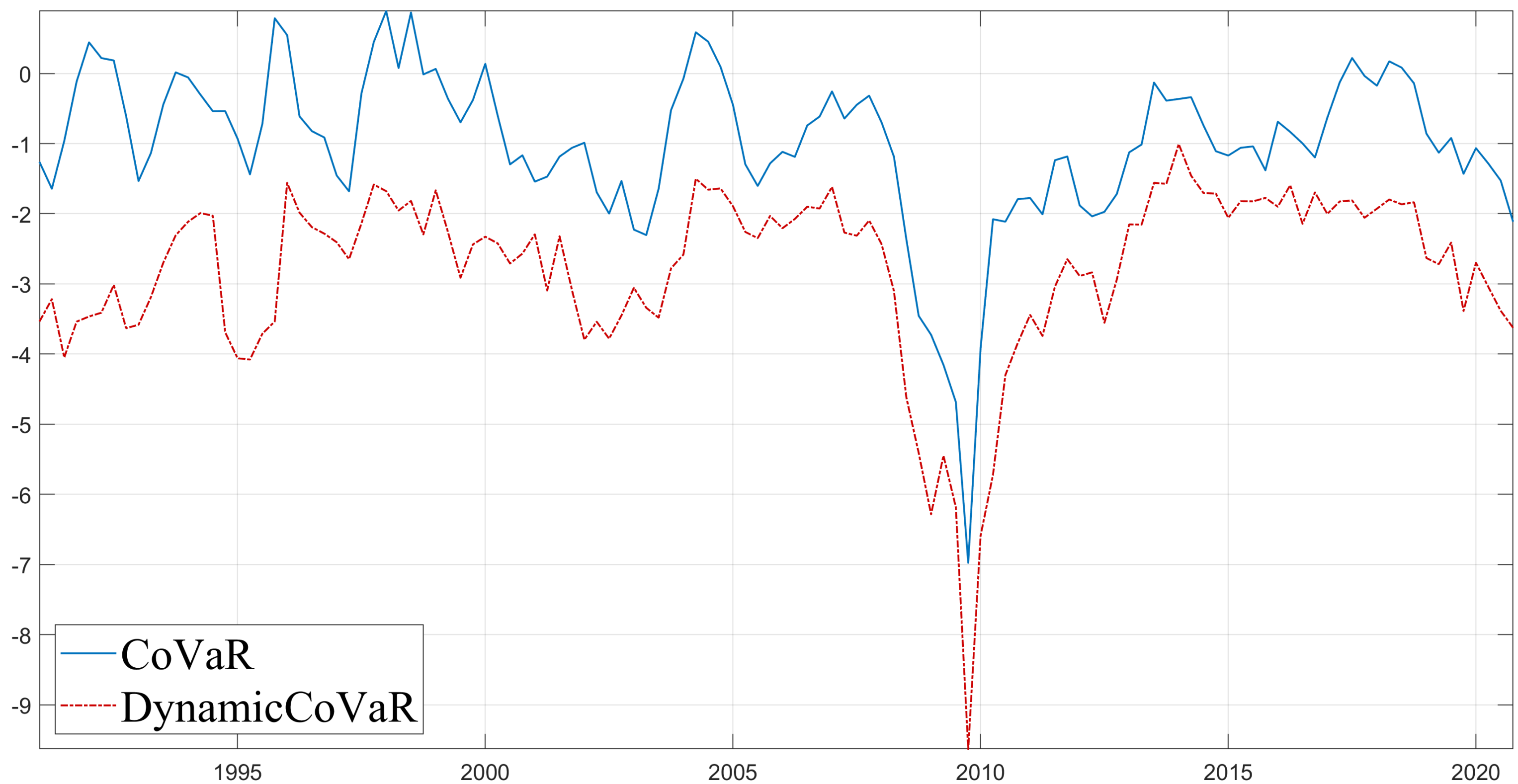
In both cases, it does not seem that lagging the state variables, institution characteristics and additional institution characteristics seems to improve the countercyclical prediction of the DCoVaR measure. However, it is likely that this is a reflection of the DCoVaR already incorporating the countercyclical component, in terms of reflecting the large losses, before they materialize, in the standard case. Recall, again, what we saw in Figure 1.9. As we can see, the large market equity losses during the 2008 financial crisis materialize after the large decrease given by the DCoVaR. As a result, it is likely that, since the procyclicality component is already captured in the standard scenario by the DCoVaR, lagging the independent variables does not seem to add any benefits to the model.

Figure 1.19: CoVaR Functions - balance sheet+VaR data, lagged 1 quarter (h=1)



Notes: The CoVaR refers to the model of [Adrian and Brunnermeier, 2016] (blue line); while the DCoVaR refers to the Dynamic CoVaR proposed in the body of the paper (red-dashed line), with balance sheet data, lagged for 1 quarter (h = 1), for different significance levels, for the weighted-average of the largest 10 financial institutions. The variables are expressed in units of total 4 quarter market returns at a quarterly frequency (standardized).

Figure 1.20: CoVaR Functions - balance sheet+VaR data, lagged 4 quarters (h=4)



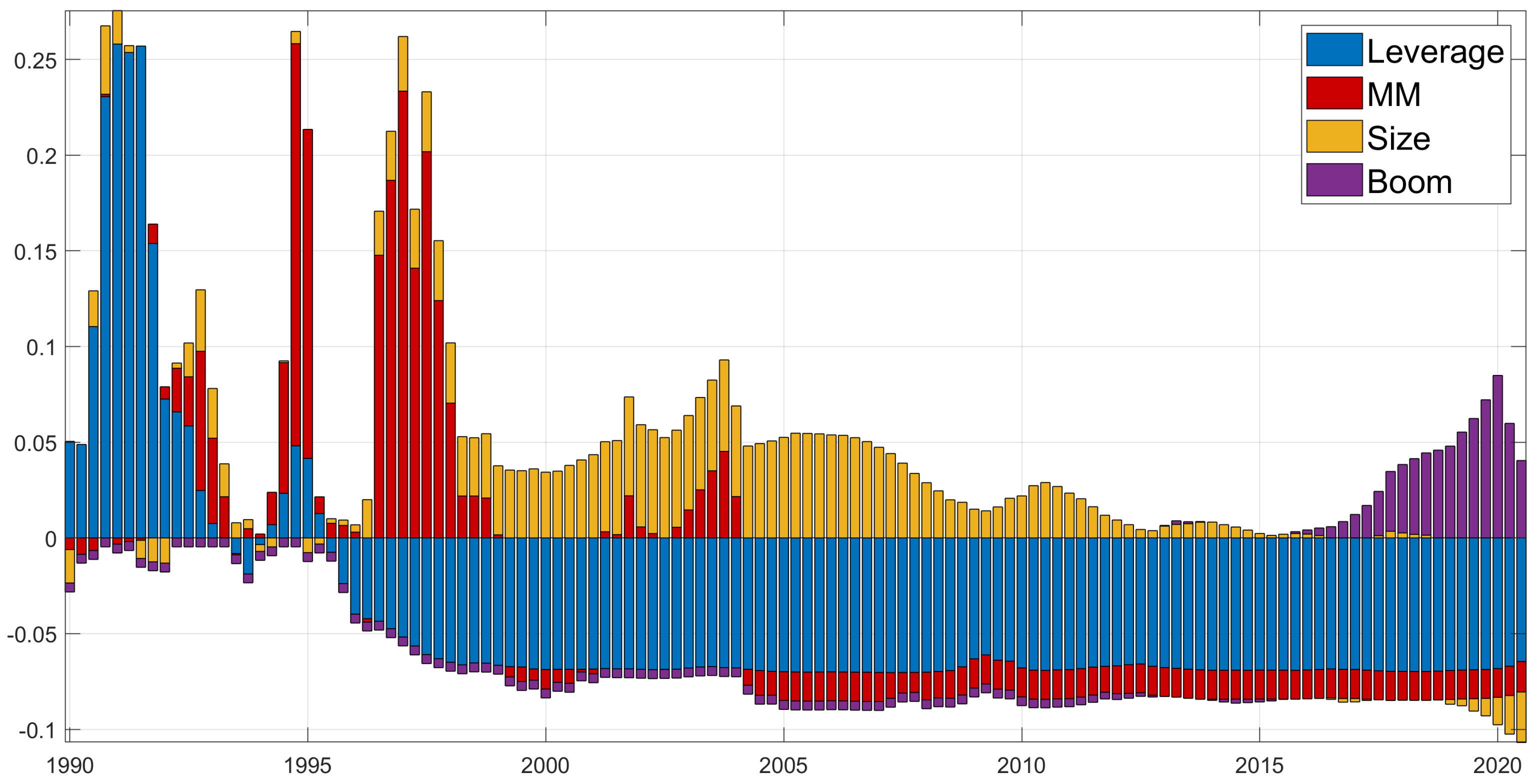
Notes: The CoVaR refers to the model of [Adrian and Brunnermeier, 2016] (blue line); while the DCoVaR refers to the Dynamic CoVaR proposed in the body of the paper (red-dashed line), with balance sheet data, lagged for 4 quarters (h = 4), for the weighted-average of the largest 10 financial institutions. The variables are expressed in units of total 4 quarter market returns at a quarterly frequency (standardized).

1.8.3 Impact Component Review

In this subsection, we seek to make a similar analysis of subsection 1.6.2, but more focused on the main 4 additional characteristics: leverage, maturity mismatch, size and boom. As before, with the study for the impact of the state variables, we focus on the effect in the case with the time-varying component, that is, in the DynamicCoVaR, for which the results are shown in Figure 1.21. Overall, the inclusion of the 4 main institution characteristics does not seem to hold a large impact on the estimations, since they are within the -0.1 and 0.25 bounds, which is consistent with the analysis we provided before, comparing Figure 1.15 and Figure 1.18. The more relevant component throughout the series seems to be leverage, while the maturity mismatch seems to be more relevant between 1995 and 2000, the size was more relevant between 2000 and 2010, and the Boom variable becomes more relevant in more recent years.

Interestingly, the leverage seems to counter the effects of systemic risk during the 90's, pointing to an accumulation of resources during this period, while there was a reversal of the variable after 1995, where it appears to hold a relatively significant impact, compared with the remaining variables, on systemic risk. Also, notice that the size variable holds a positive effect, countering systemic risk. The model seems to be implying that the size of financial institutions makes them more robust and resistant to any shocks that may affect them, making them contribute less to systemic risk. Could this be contradictory to our previous evidence on the values of the β rising with market capitalization? Not quite, and in fact, quite the opposite. Notice that this is consistent with the evidence we found in subsection 1.6.3, where the top 10 financial institutions contributing to systemic risk where not necessarily the largest ones. When we combine these results with those obtained in subsections 1.6.3 and 1.6.4, the model appears to be encapsulating the potential positive effects of dimension on the size variable (that is, that larger financial institutions become more robust to different shocks, contributing less to systemic risk), while the β captures the potential negative effects (if the specific financial institution enters into financial distress, the larger it is, the higher the effect on systemic risk). Additionally, notice that this was the case before the 2008 financial crisis. After, the size variable decreases significantly, incorporating the information that even large financial institutions were exposed. Finally, the Boom variable seems to have a higher relevance for the more recent years, possibly reflecting the market concentration impact of the COVID-19 pandemic, that is, the financial institutions doing well before the pandemic have done even better during the pandemic.

Figure 1.21: Institution characteristics: components



Notes: This figure illustrates the impact of the institution characteristics on the DynamicCoVaR(DCoVaR). The impact of the different components is given by the leverage (blue bar); the maturity mismatch ('MM',red bar), the size (yellow bar), and Boom (purple bar), for the weighted-average of the largest 10 financial institutions. The variables are expressed in units of total 4 quarter market returns at a quarter frequency (standardized).

1.8.4 Forecast Review

In this subsection, we review the forecasting analysis that we made in subsection 1.6.5, when adding the institution characteristics and additional institution characteristics into the model. The results can be observed in Table 1.11. We can see that, when adding the balance sheet data into both models, it seems that the standard model outperforms our model for the majority of cases. This is clearly the case for the average lengths (L) indicator, since the values of the standard model are always negative, and the values of the tvp model are always positive, which yields a complete reversal of the results we obtained before. As for the average empirical coverage (C), the results seem to favor the standard model. In the tvp model, almost all scenarios lead to a value equal to 1. And even though they could be closer to the nominal coverage, it would seem to be simply by accident. The tick loss (TL) indicator also seems to favour the standard model, with the estimated values being lower than the tvp model. And, unlike before, the forecasting performance of the tvp model compared with the standard model does not seem to improve with the increase in h.

However, we should consider the following 2 points: 1 - For the scenario of h = 8 (2 years forecast horizon), it seems that the average empirical coverage (C) and tick loss (TL) indicators point to better results of the tvp model, instead of the standard model. Although this could simply be an exception, it should also lead to caution about preferring the standard model for forecasting; 2 - not only that, if we also consider that the Diebold-Mariano tests only find statistical significance in the h = 8 scenario, where the tick loss (TL) indicator points to an outperformance of the tvp model over the standard model, it casts further doubt on the choice of a specific model in terms of forecasting.

It seems clear that the inclusion of balance sheet data has led to a worse performance of the tvp model, but what about the standard model? We can make a general comparison between the conclusions of each indicator for the standard model with balance sheet data, and the standard model without it. However, the differences could also be connected to the different horizons considered, due to the change from weekly to quarterly frequency. The other option is to make a direct comparison between the first quarterly scenario (h =1), and the h = 15 in the weekly frequency scenario (in Table 1.9), since 1 quarter is approximately 14 weeks, and is closest to the 15 weeks scenario. In either option, we find evidence of clear improvement of the average lengths (L) indicator, while the average empirical coverage (C) also appears to have some improvement for most scenarios, with the exception of $\tau = 0.01$, which shows worse outcomes. This is also the case for the tick loss (TL) indicator, where most cases show an improvement of the forecast ability of the standard model with the inclusion of balance sheet data.

In conclusion, when considering the institution characteristics and the additional institution characteristics in the models, the standard model has an improvement of its forecasting ability, while the reverse change occurred for the tvp model. And although this points in the direction of the standard model being preferred in comparison to the tvp model, in terms of forecast ability, recall that for the scenario of h = 8 (2 years forecast horizon), it seems that the average empirical coverage (C) and tick loss (TL) indicators point to better results of the tvp model, instead of the standard model, and that the Diebold-Mariano tests only find statistical significance in the h = 8 scenario, where the tick loss (TL) indicator points to an outperformance of the tvp model over the standard model. So, the results for the choice of one model over the other are not conclusive, but certainly shift in the direction of the standard model.

Again, we see the results in this subsection as supporting the forecast ability of more parsimonious models. With the standard model being more parsimonious, it was expected that the tvp model would have a worse performance when adding the balance sheet data, while the standard model would either have an improvement of its performance (which seems to be the case), or the decrease in its performance would be lower than the tvp model. It is highly likely that the introduction of time-varying parameters into the standard model would make their estimation more sensitive to even further inclusion of additional elements. When introducing 13 new variables, which, in addition, are different for each financial institution in the sample, it was expected that it would shift our tvp model further away from a parsimonious model.

1.9 Conclusion

The past decade has spawned an outpouring of articles and books on how to measure systemic risk. In their influential paper, [Adrian and Brunnermeier, 2016] lay the foundations of what became one of the most popular measures of systemic risk, the Conditional Value at Risk (in short, CoVaR). One of the most appealing features of the CoVaR is its ability of capturing both the cross-section and time series dimension of systemic risk. However, the dynamics of the time-varying CoVaR are entirely due to the behaviour of the state variables. Without their inclusion, the CoVaR would be constant over time.

The key contribution of this paper is to relax the assumption of a time-invariant tail dependence between the financial system and each institution's losses. The parameters governing the relationship between state variables and tail risk are also allowed to vary with time, giving the model additional flexibility. Our starting point is an estimated quantile regression that replicates the results presented by [Adrian and Brunnermeier, 2016]. We then extend this baseline specification so as to accommodate time-varying parameters. This allows us to estimate a quantile regression with time-varying parameters, a technology which is new and may be useful for future research in measuring tail risk.

Our results show that the estimations for the VaR are exceedingly similar between the two models, and we can infer that the dynamic component that we introduced does not affect the estimations for the risk of individual financial institutions. On the other hand, the estimations for the CoVaR are starkly different, reflecting the influence of the dynamic component on systemic risk analysis instead. In fact, the introduction of time-varying parameters leads to an increase of the volatility of the CoVaR values. Not only that, the procyclical nature of systemic risk becomes more pronounced, compared to the original model. As expected, this is likely due to the introduction of additional sources of risk: that tail dependency between the loss distributions of the financial system and of each individual institution can change over time, as well as the effect between state variables and tail risk. More specifically, with the introduction of the dynamic component into the model, we can conclude that they result from the changes of the impact of the state variables on the dependent variable (systemic risk) over time, or from the change of the impact of the individual risk of each institution in the systemic risk over time (or a combination of both). The first scenario would point to the exposure of the financial system to macroeconomic conditions changing overtime, while the second scenario would imply changes in the conditions within the financial sector itself.

We attempt to further isolate the contribution of each variable. When we separate between the effect of the VaR (idiosyncratic risk) and the effect of the state variables, we find that both elements are relevant for the CoVaR (systemic risk) in both models, with the VaR being the main component in our dynamic model for the explanation of the DCoVaR (DynamicCoVaR). When we further attempt to infer on the different impact of the state variables in our dynamic model framework, we find that 3 main variables are the most relevant: equity volatility, the change in the slope of the yield curve, and the TED spread. Moreover, we further isolated their impact, by separating between the change in the values of the variables and the change in the dynamic estimated coefficients. The regressors associated with the VaR, the change in the slope of the yield curve and equity volatility seem to show the more significant changes, and can serve as early warning signals for systemic risk. Notice that 2 out of the 3 match the main impact of the state variables. This would imply that the large significance of the changes in systemic risk in those 2 state variables are given by changes in the estimated coefficients, and not necessarily due to changes in the state variables.

In what regards the contribution of each financial institution to systemic risk, we take 3 different approaches: 1 - sum of overall values of losses; 2 - volatility contribution to the series; 3 - contribution to losses in periods of crisis. We focus the analysis on the top 10 financial institutions in each scenario, for both the standard model and the tvp model. Although the institutions in each list change, there are some who consistently make the top 10, including Morgan Stanley, Keycorp, and Charles Schwab. This contribution seems to increase with market capitalization, leading to larger financial institutions contributing more to systemic risk. When testing for the influence of outliers, we verify that our results are robust to their presence in the series, since they do not change significantly when the estimations exclude them.

In terms of forecasting, the accuracy of our model increases with h, the horizon in number of weeks, and also with τ, the specific quantile considered. For the short term (h between 4 and 12 weeks), there is not an outperformance of one of the models over the other, as the different evaluation statistics point to different models, for different scenarios. One of the possible explanations is that, traditionally, more parsimonious models are able to achieve better forecasting results, since they are less likely to overfit the original dataset. Nevertheless, even for the short term, this does not lead to the standard model achieving better results, in terms of forecasting. On the other hand, for the medium (between 15 and 25 weeks) and the long term (between 30 and 40 weeks), there is a clear outperformance of our model over the standard model. With a higher τ, more information is taken into account, improving the reliability and the forecasting performance of our model, while a lower τ would force the model to focus only on very extreme scenarios, implying it is only considering a small subsample, where few elements would be taken into account for the estimation.

In order to consider additional sources of risk, we add balance sheet data into both models, in which the 4 main components consist of leverage, maturity mismatch, size, and a boom indicator. Unlike before, the introduction of these additional variables has an impact on idiosyncratic risk (VaR vs DVaR estimations). This is likely connected to these variables being idiosyncratic across different financial institutions, while the variables we had in the standard scenario (the state variables), where equivalent amongst them. It also introduces additional volatility into both series, and, generally, reflects more conservatives/negative estimates of our DCoVaR, relative to the standard model, when compared to the standard scenario. When further inspecting the influence of each variable, we conclude that leverage consistently holds a significant effect throughout the series, while the relevance of the other 3 components depends on the specific timeline of analysis. More specifically, the maturity mismatch reflects higher relevance between 1995 and 2000, the size was more relevant between 2000 and 2010, and the Boom variable becomes more relevant in more recent years.

Interestingly enough, the size variable holds a positive effect, countering systemic risk. It would seem that the model appears to be encapsulating the potential positive effects of dimension on the size variable (that is, that larger financial institutions become more robust and resistant to any shocks that may affect them, making them contribute less to systemic risk), while the β captures the potential negative effects (if the specific financial institution enters into financial distress, the larger it is, the higher the effect on systemic risk).

Adding balance sheet data has opposite effects in each model, in terms of forecasting accuracy. Our forecasting results worsen for the model with time-varying parameters, but improve for the standard model, even though there is no clear outperformance of one over the other. As expected, as more information is added to the model, and it becomes more complex, the results favor the forecasting ability of more parsimonious models. When introducing 13 new variables, which, in addition, are different for each financial institution in the sample, it was expected that it would shift our tvp model further away from a parsimonious model. Nevertheless, there is no outperformance of either model in this scenario.

1.10 Appendix

1.10.1 Algorithm for Posterior Inference

In this section we discuss how to extend the Gibbs Sampler proposed by [Kozumi and Kobayashi, 2011] to allow for time-varying parameters in a quantile regression.

Let us write the quantile regression (1.17) in state space form as follows

$$y_t = \mathbf{w}_t' \delta_{q,t} + \varepsilon_t, \tag{1.40}$$
$$\delta_{q,t} = \delta_{q,t-1} + \xi_t. \tag{1.41}$$

Where $\mathbf{w}_t = [\mathbf{x}_t', \theta z_t]$ and $\delta_{q,t} = [\beta_{q,t}, 1]$. In addition, $\varepsilon_t \sim N(0,R)$ and $\xi_t \sim N(0,\Omega)$ where $R = \phi^2 z_t$. The strategy consists in augmenting the state vector $\beta_{q,t}$ in the original model (1.17)-(1.18) with an additional parameter with zero measurement noise which is set to 1. Thus, we set the variance of the last element of the new state vector $\delta_{q,t}$ to zero. Therefore, Ω is an augmented version of Q with one additional row and column of zeros. The state space representation of the quantile regression in the form (1.40)-(1.41) allows us to carry out Bayesian inference with the methods introduced by [Carter and Kohn, 1994]. Estimation proceeds in a standard way by sampling for each quantile q sequentially from the following conditional densities:

1. Sample $\delta_{q,t}|\delta_{q,t-1}, \Omega, R, y_t, \mathbf{x}_t, z_t$ for all $t = \{1, ..., T\}$ using the [Carter and Kohn, 1994] filter and smoother for state-space models which proceeds as follows. Given that $\delta_{q,t} \sim N(\delta_{q,t|s}, P_{t|s})$ where $\delta_{q,t|s}$ and $P_{t|s}$ are the expected value and variance of $\delta_{q,t}$ for data up to time s, the Kalman filter recursions yield the filtered states:

$$\begin{aligned}
\delta_{q,t|t-1} &= \delta_{q,t-1|t-1} \\
P_{t|t-1} &= P_{t-1|t-1} + \Omega \\
K_t &= P_{t|t-1}\mathbf{w}_t(\mathbf{w}_t P_{t|t-1}\mathbf{w}_t' + R)^{-1} \\
\delta_{q,t|t} &= \delta_{q,t|t-1} + K_t(y_t - \mathbf{w}_t'\delta_{q,t|t-1}) \\
P_{t|t} &= P_{t|t-1} - K_t\mathbf{w}_t' P_{t|t-1}
\end{aligned}$$

   The recursion is initialized with the starting values $\delta_{q,0|0} = \delta_{q,0}$ and $P_{0|0} = V_0^*$, which are constructed by augmenting the priors for $\beta_{q,0}$ so that they are consistent with the state space representation. The last elements of the recursion are used to obtain a single draw $\delta_{q,T}$. For periods $T-1, ..., 1$ we smooth the initial estimates by using information from later periods. This is done by running backward recursions for $t = T-1, ..., 1$:

$$\begin{aligned}
\delta_{q,t|t+1} &= \delta_{q,t|t} + P_{t|t}P_{t+1|t}'(\delta_{q,t+1} - \delta_{q,t|t}) \\
P_{t|t+1} &= P_{t|t} - P_{t|t}P_{t+1|t}'P_{t|t}
\end{aligned}$$

We can then draw from the posterior of $\delta_{q,t}$ which is a Normal pdf with mean $\delta_{q,t|t+1}$ and variance $P_{t|t+1}$.

2. Sample $z_t|\delta_{q,t},\Omega,y_t,\mathbf{x}_t \sim \mathscr{GIG}(\frac{1}{2},a,b)$
with $a = (y_t - \mathbf{x}_t'\beta_{q,t})/\phi$ and $b = (2+\theta^2/\phi^2)^{1/2}$.

Where the probability function of $\mathscr{GIG}(v,a,b)$ is given by

$$f(x|v,a,b) = \frac{(b/a)^v}{2K_v(ab)} x^{v-1} exp\left\{ -\frac{1}{2}(a^2x^{-1}+b^2x)\right\}, x>0, a,b \geq 0, v \in \mathbb{R},$$

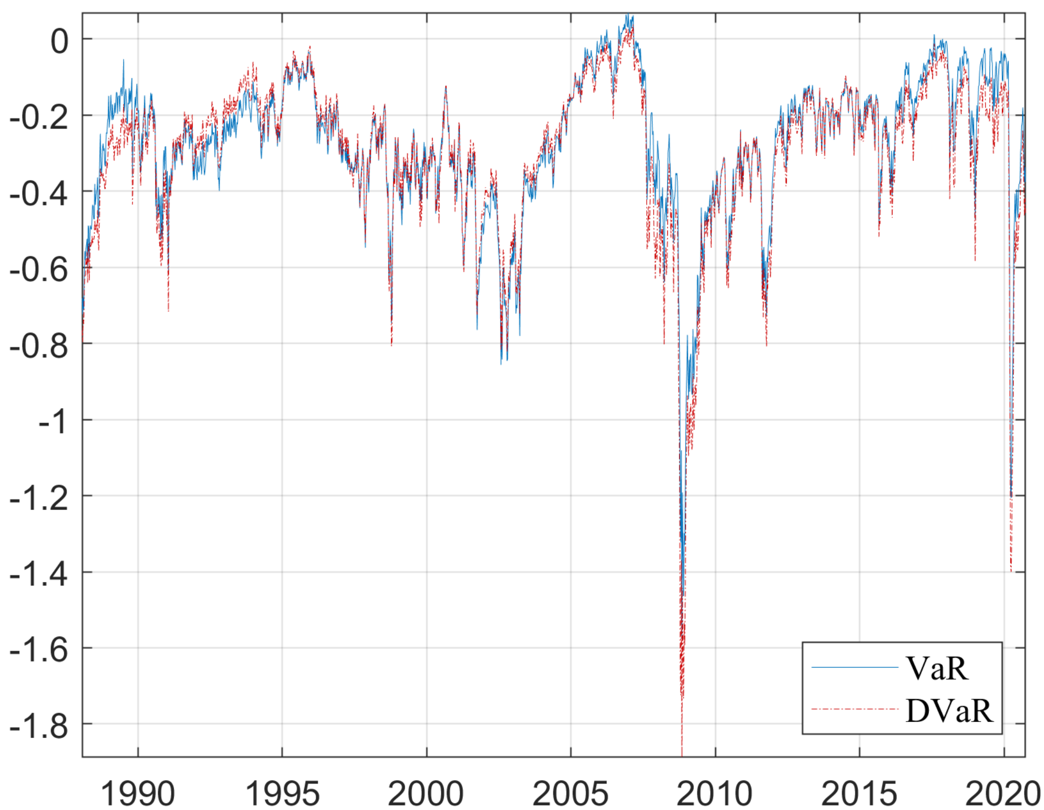
and $K_v(.)$ is a modified Bessel function of the third kind [13].

3. Sample $Q^{-1}|\delta_{q,t},y_t,\mathbf{x}_t,z_t \sim \mathscr{W}(S,W^{-1})$.
With $S = T+s$ and $W^{-1} = (w+\sum_{t=1}^{T}(\beta_t-\beta_{t-1})'(\beta_t-\beta_{t-1}))^{-1}$.

1.10.2 Additional Tables and Figures

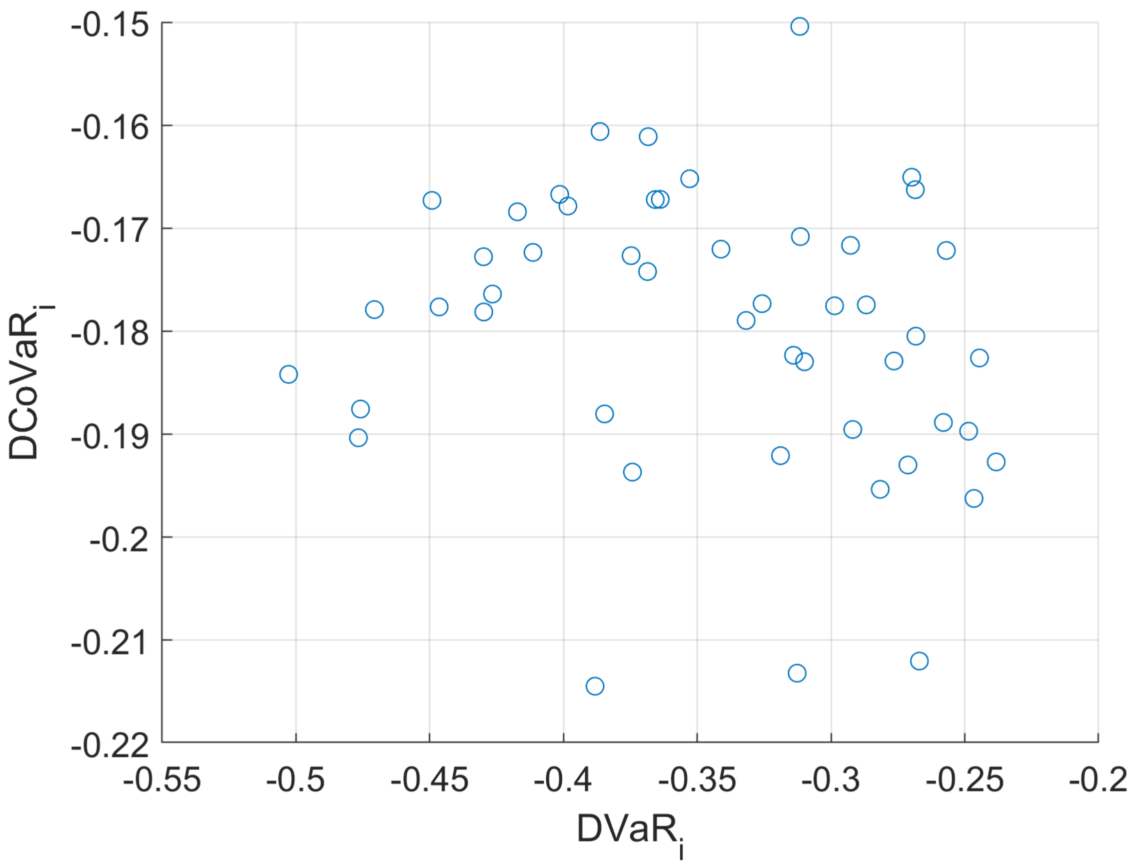
[13] see [Kozumi and Kobayashi, 2011] pp.4 for more details

Figure 1.22: VaR Functions



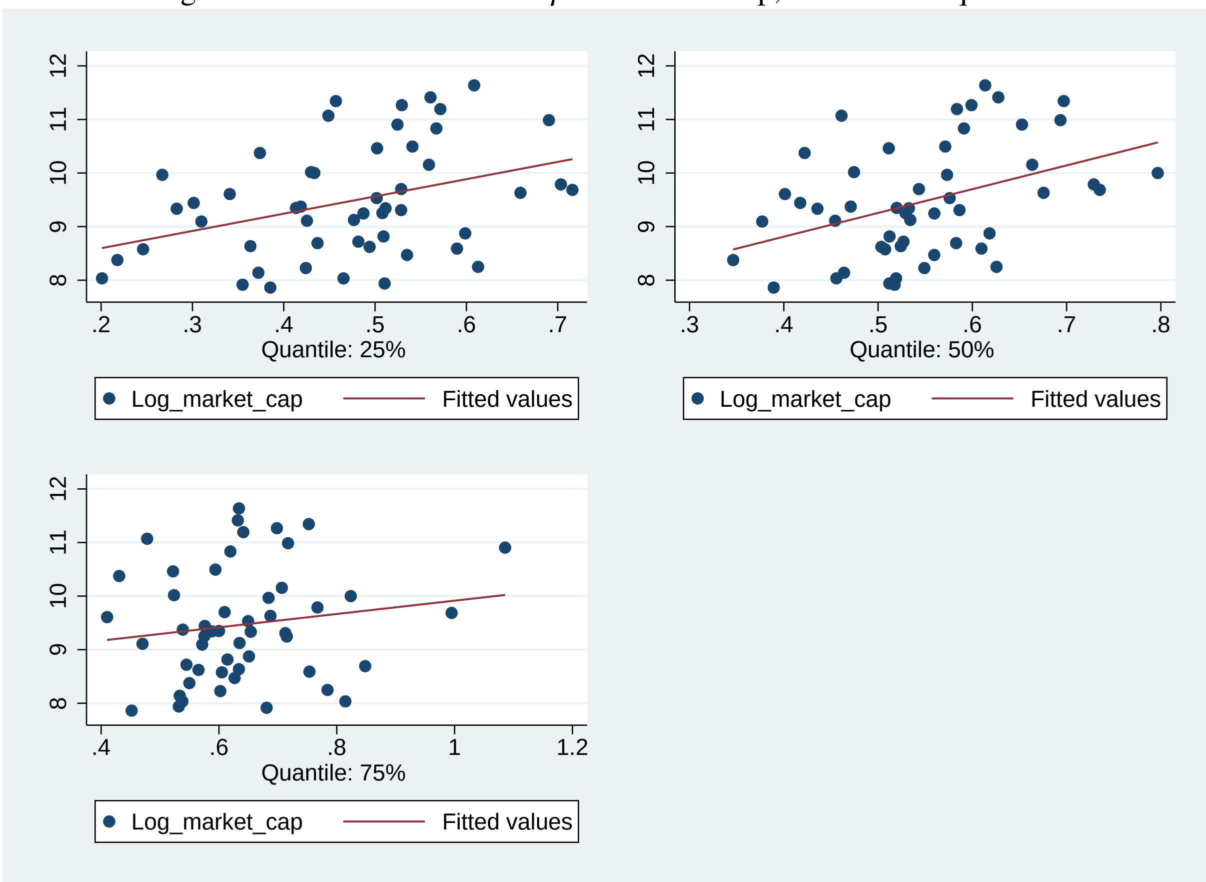
Notes: This Figure shows the comparison between the institutions' individual risk, in the traditional model (VaR, in blue) and in the dynamic model (DVaR, in red), for the average of the largest 10 financial institutions. The variables are expressed in units of total 52 week market returns at a weekly frequency.

Figure 1.23: Cross-section Analysis of DVaR and DCoVaR



Notes: This Figure shows the weak correlation between the institutions' individual risk, given by the DVaR, and the systemic risk, given by the DCoVaR, for all financial institutions in the sample. The variables are expressed in units of total 52 week market returns at a weekly frequency.

Figure 1.24: Relation between β and market cap, for different quantiles



Notes: Each Figure reflects the relationship between the estimated β and market capitalization, for 25%, 50% and 75% quantiles of the overall distribution. Each point corresponds to each financial institution in our sample. The market cap is expressed in billions of US $ dollars.

Table 1.1: State Variable Summary Statistics

	Mean	Std. Dev.	Skewness	Min.	Max	1% Stress
Three month yield change	-0.20	20.33	-0.76	-182.00	192.00	-65.22
Term spread change	0.56	42.53	2.22	-76.60	407.50	13.80
TED spread	1.75	112.17	-0.13	10.20	476.40	371.38
Credit spread change	0.03	7.30	-43.50	1.75	73.90	21.42
Market return	0.03	1.07	-0.65	-20.47	11.58	-2.87
Equity Volatility	20.15	9.03	2.54	7.54	113.03	9.04

Notes: The spreads and spread changes are expressed in weekly basis points, and returns are in weekly percent. The 1 percent stress in the last column corresponds to the state variable realizations in the worst 1 percent of financial system returns.

Table 1.2: Quarterly Summary Statistics

	Mean	Std. Dev.	Obs.	Obs. (%)
Leverage	8.06	9.98	8331	98.28%
Maturity Mismatch	-7.81	16.34	5768	68.04%
Size	0.91	0.16	8334	98.31%
Boom	0.62	3.95	8475	99.98%

Notes: The table reports summary statistics when we include the institution characteristics into the model. We consider the same sample period and financial institutions as in the original set. The % of the observations are defined in terms of the overall sample of institutions characteristics obtained from the WRDS.

Table 1.3: Chronological analysis of the main negative extreme economic/financial events

Timeline	**Extreme Market Event**	**Source/Classification**	**Markets**
1636	Dutch Tulip Crisis	Asset (Price) Bubbles	Europe
1720	South Street Sea Bubble	Speculation	Europe
1763	End of Seven Years War	Asset Bubbles	Amsterdam
1825	Crisis of 1825–1826	Sovereign Bond Default	Europe, Latin America
1837	Crisis of 1836–1839	Cotton Prices	England, United States
1857	Hamburg Crisis of 1857	Credit Expansion	Hamburg, Sweden
1873	Panic of 1873	International Contagion	U.S., Austria, Germany
1907	Panic of 1907	Banking Crisis	across assets/markets
1929	Great Depression	Banking Crisis	U.S., Europe
1977	"Big Five" Crisis	Real Estate Bubble, Banking Crisis	Spain
1980's	Debt Crisis of the 1980's	Sovereign Bond Default, Currency Crash	US
1987	"Big Five" Crisis	Real Estate Bubble/ Banking Crisis	Norway
1990's	"Big Five" Crisis	Real Estate Bubble/ Banking Crisis	Finland, Sweden, Japan
1990's	Latin American Crisis	Sovereign Bond Default	Latin America
1994	Mexican Debt Crisis	Currency/Banking Crisis	Mexico
1997	East Asian Financial Crisis	Currency Crash	Asia
1998	Long-Term Capital Mgt.	Ruble, Money Market	US
2000	Dot-Com Tech Bubble	Asset Bubble	US, World Wide
2008	Global Financial Crisis (GFC)	Asset Bubble, Credit Expansion	US, World Wide
2009	Dubai's "Debt Standstill"	GFC, Real Estate Bubble Burst, Credit Expansion	US, most currencies other than US$
2010	European Debt Crisis (EDC)	Real Estate Bubble, Banking Crises, Sovereign Debt	European bond markets
2011	"August 2011 Stock markets fall"	EDC of 2010	US, Europe, Middle East, rest of Asia
2015–16	Chinese Equity Market Crash	Asset Bubbles	China, US
2018	Global Equity Market Downturn	Asset Bubbles	US
2020	March 2020 Crash	Zoonotic	US

Source: Table A1 from [Chakraborty et al., 2021]

Table 1.4: Ranking of systemic risk contribution

Sum	**Standard deviation**	**Crisis**
QR(baseline)	QR(baseline)	QR(baseline)
MARSH & MCLENNAN	CHUBB	PEOPLES UNITED FINANCIAL
HUNTINGTON BCSH.	HUNTINGTON BCSH	CHUBB
STATE STREET	ALLSTATE ORD SHS	BERKSHIRE HATHAWAY
BANK OF NEW YORK MELLON	BERKSHIRE HATHAWAY	CITIGROUP
PROGRESSIVE OHIO	UNUM GROUP	ALLSTATE ORD SHS
AMERICAN INTL.GP.	KEYCORP	KEYCORP
TRAVELERS COS.	TRUIST FINANCIAL	CHARLES SCHWAB
AFLAC	PEOPLES UNITED FINANCIAL	SVB FINANCIAL GROUP
GLOBE LIFE	BANK OF NEW YORK MELLON	REGIONS FINL.NEW
TRUIST FINANCIAL	MORGAN STANLEY	HUNTINGTON BCSH.
QR(TVP)	QR(TVP)	QR(TVP)
PROGRESSIVE OHIO	NORTHERN TRUST	CHUBB
AFLAC	MORGAN STANLEY	CAPITAL ONE FINL
ARTHUR J GALLAGHER	CAPITAL ONE FINL	FRANKLIN RESOURCES
S&P GLOBAL	CHUBB	COMERICA
PEOPLES UNITED FINANCIAL	BERKSHIRE HATHAWAY	CHARLES SCHWAB
MARSH & MCLENNAN	GLOBE LIFE	MORGAN STANLEY
W R BERKLEY	T ROWE PRICE GROUP	BERKSHIRE HATHAWAY
CINCINNATI FINL.	COMERICA	ZIONS BANCORP.
GLOBE LIFE	TRUIST FINANCIAL	FIFTH THIRD BANCORP
US BANCORP	CHARLES SCHWAB	KEYCORP

Notes: The Sum, standard deviation, and crisis indicators are computed for each model considered. QR(baseline) refers to the quantile regression for the standard model of [Adrian and Brunnermeier, 2016], while the QR(TVP) refers to the quantile regression with the time-varying parameters model.

Table 1.5: Ranking of systemic risk contribution, weighted by market equity

Sum	**Standard deviation**	**Crisis**
QR(baseline)	QR(baseline)	QR(baseline)
JP MORGAN	BERKSHIRE HATHAWAY	BERKSHIRE HATHAWAY
BANK OF AMERICA	JP MORGAN	JP MORGAN
BERKSHIRE HATHAWAY	BANK OF AMERICA	BANK OF AMERICA
WELLS FARGO	MORGAN STANLEY	CITIGROUP
CITIGROUP	CITIGROUP	BLACKROCK
S&P GLOBAL	WELLS FARGO	WELLS FARGO
AMERICAN EXPRESS	BLACKROCK	MORGAN STANLEY
MORGAN STANLEY	CHARLES SCHWAB	CHARLES SCHWAB
CHARLES SCHWAB	S&P GLOBAL	CHUBB
MARSH & MCLENNAN	CHUBB	S&P GLOBAL
QR(TVP)	QR(TVP)	QR(TVP)
JP MORGAN	BERKSHIRE HATHAWAY	BERKSHIRE HATHAWAY
BERKSHIRE HATHAWAY	JP MORGAN	JP MORGAN
BANK OF AMERICA	BANK OF AMERICA	BANK OF AMERICA
S&P GLOBAL	MORGAN STANLEY	MORGAN STANLEY
WELLS FARGO	BLACKROCK	BLACKROCK
AMERICAN EXPRESS	WELLS FARGO	CHARLES SCHWAB
CITIGROUP	CITIGROUP	CHUBB
CHARLES SCHWAB	CHARLES SCHWAB	CITIGROUP
MORGAN STANLEY	S&P GLOBAL	WELLS FARGO
PROGRESSIVE OHIO	AMERICAN EXPRESS	S&P GLOBAL

Notes: The Sum, standard deviation, and crisis indicators are computed for each model considered. QR(baseline) refers to the quantile regression for the standard model of [Adrian and Brunnermeier, 2016], while the QR(TVP) refers to the quantile regression with the time-varying parameters model.

Table 1.6: Overall results for the impact of idiosyncratic risk on systemic risk

IC	β_{VaR}^{CoVaR}	$\beta_{VaR}^{DCoVaR}*$			Market Cap*
		25%	50%	75%	
JP Morgan	0.5585	0.4571	0.6970	0.7526	84,419.26
Berkshire Hathaway	0.6336	0.5607	0.6276	0.6321	90,494.62
Bank of America	0.5812	0.5293	0.5991	0.6984	78,267.37
Citigroup	0.6077	0.6085	0.6137	0.6340	113,175.38
Wells Fargo	0.6133	0.5715	0.5837	0.6414	72,673.12
Goldman Sachs	0.3468	0.4489	0.4612	0.4781	64,238.88
Morgan Stanley	0.6078	0.5671	0.5911	0.6195	50,683.36
Charles Schwab	0.3159	0.2670	0.5732	0.6843	21,302.51
S&P GLOBAL	0.4355	0.4134	0.5198	0.6002	11,485.25
Chubb	0.5419	0.4299	0.4745	0.5238	22,402.75
American Express	0.5495	0.5409	0.5713	0.5941	36,130.48
Blackrock	0.3689	0.3739	0.4221	0.4307	32,034.21
AON	0.2858	0.2828	0.4357	0.6540	11,314.96
PNC	0.5628	0.5286	0.5434	0.6097	16,328.39
Travelers	0.4407	0.3014	0.4174	0.5760	12,609.70
Marsh & McLennan	0.6009	0.5018	0.5760	0.6496	13,795.78
US Bancorp	0.5158	0.5022	0.5114	0.5221	34,967.27
Bank of New York	0.6933	0.7035	0.7289	0.7673	17,822.35
Moody's	0.4047	0.3409	0.4012	0.4102	14,881.18
Capital One	0.4743	0.4335	0.7967	0.8238	22,029.85
Truist Financial	0.5489	0.5115	0.5327	0.5880	11,402.82
AFLAC	0.4446	0.4187	0.4710	0.5386	11,776.92
American Intern. Group	0.5361	0.5245	0.6527	1.0857	54,436.75
Progressive	0.4307	0.4254	0.4545	0.4703	9,039.44
Arthur J Gallagher	0.4063	0.3722	0.4639	0.5335	3,426.06
Allstate	0.6691	0.5590	0.6636	0.7068	25,705.75
State Street	0.6696	0.5285	0.5864	0.7128	11,027.54
Franklin Templeton	0.4481	0.5080	0.5291	0.5753	10,436.35
M&T Bank	0.4890	0.4817	0.5270	0.5449	6,119.14
Hartford	0.6936	0.6592	0.6756	0.6875	15,229.27

Table 1.7: *

Table 1.6 (continued): Overall results for systemic risk, and the impact of idiosyncratic risk

IC	β_{VaR}^{CoVaR}	β_{VaR}^{DCoVaR}*			Market Cap*
		25%	50%	75%	
Regions Financial Corp	0.4622	0.4940	0.5035	0.5654	5,550.01
Everest	0.3807	0.2460	0.5075	0.6050	5,307.60
Keycorp	0.4815	0.5093	0.5122	0.6145	6,745.14
Comerica	0.5342	0.5350	0.5596	0.6266	4,772.03
Unum	0.4707	0.3635	0.5241	0.6339	5,625.48
Lincoln	0.4682	0.4370	0.5828	0.8483	5,955.41
Raymond James	0.4851	0.4655	0.5191	0.5380	3,084.14
WR Berkley	0.4478	0.3853	0.3893	0.4519	2,598.28
Globe Life	0.4542	0.4242	0.5491	0.6023	3,739.05
Loews	0.3162	0.3098	0.3771	0.5716	8,912.63
T Rowe Price	0.5582	0.4769	0.5342	0.6350	9,176.38
Silicon Valley Bank	0.3668	0.3549	0.5176	0.6810	2,739.80
Fifth Third Bank	0.3769	0.4873	0.5597	0.7152	10,358.93
Peoples United	0.2771	0.2010	0.4558	0.8146	3,087.19
Cincinnati Financial	0.3542	0.2178	0.3463	0.5498	4,342.24
Northers Trust	0.6145	0.5987	0.6183	0.6510	7,142.43
Huntington Bancshares	0.6132	0.6128	0.6257	0.7844	3,821.13
Zions Bancorp	0.4821	0.5105	0.5120	0.5319	2,804.63
Top 10	0.6957	0.6904	0.6935	0.7173	59,066.56
Bottom 10	0.5926	0.5897	0.6097	0.7537	5,378.06
Middle 10	0.7411	0.7161	0.7352	0.9950	16,077.28

Notes: The table is composed by a total of 4 elements: 1 - IC, which provides the name of each financial institution in the sample; 2 - β_{VaR}^{CoVaR}, that gives information on the estimated regressor for the impact of the VaR (idiosyncratic risk) on the CoVaR (systemic risk), in the original [Adrian and Brunnermeier, 2016] model (recall that this regressor is constant overtime); 3 - β_{VaR}^{DCoVaR}, which is the same as the previous case, but for our time-varying parameter model. In this case, we also separate between the 25%, 50% and 75% quantiles of the overall distribution; 4 - Market Cap refers to the market capitalization. All elements with "*" are calculated as the average across the overall periods in the sample. The remaining institutions are not shown in the table due to data availability for few periods, which could decrease reliability of the results in those cases. The Market Cap is expressed in billions of US $ dollars.

Table 1.8: Forecasting Statistics (short term)

τ	0.01			0.025			0.05			0.1		
statistic	C	L	TL	C	L	TL	C	L	TL	C	L	TL
					h = 4							
QR(baseline)	0.9989	-0.65	0.0214	0.9917	-0.44	0.0469	0.9817	-0.27	0.0810	0.9552	0.13	0.1355
QR(TVP)	0.9541	-1.40	0.0233	0.8545	-1.24	0.0639	0.7731	-1.01	0.1113	0.6940	-0.54	0.1665
					h = 8							
QR(baseline)	0.9983	-0.54	0.0226	0.9917	-0.28	0.0514	0.9817	-0.21	0.0871	0.9617	0.14	0.1399
QR(TVP)	0.9823	-1.16	0.0219	0.9346	-1.07	0.0489	0.8386	-0.91	0.0917	0.7632	-0.43	0.1483
					h = 12							
QR(baseline)	0.9961	-0.66	0.0228	0.9928	-0.29	0.0526	0.9805	-0.21	0.0909	0.9611	0.14	0.1440
QR(TVP)	0.9872	-0.95	0.0224	0.9694	-0.91	0.0481	0.8938	-0.80	0.0820**	0.7893	-0.38	0.1459

Notes: Empirical coverage, Length and Tick Loss are computed for each quantile τ and forecast horizon h for each model considered. The horizon h is defined in number of weeks. QR(baseline) refers to the quantile regression for the standard model of [Adrian and Brunnermeier, 2016], while the QR(TVP) refers to the quantile regression with the time-varying parameters model. The Diebold-Mariano statistics refer to the hypothesis of superior predictive ability of the tick loss of each alternative model vis-à-vis the baseline quantile regression. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 1.9: Forecasting Statistics (medium term)

τ	0.01			0.025			0.05			0.1		
statistic	C	L	TL	C	L	TL	C	L	TL	C	L	TL
					h = 15							
QR(baseline)	0.9961	-0.61	0.0238	0.9911	-0.29	0.0535	0.9772	-0.18	0.0934	0.9555	0.13	0.1471
QR(TVP)	0.9894	-0.91	0.0233	0.9716	-0.89	0.0488	0.9558	-0.77	0.0815***	0.8724	-0.38	0.1061***
					h = 20							
QR(baseline)	0.9972	-0.55	0.0242	0.9883	-0.27	0.0551	0.9821	-0.02	0.9553	0.9617	0.20	0.1566
QR(TVP)	0.9905	-0.86	0.0235	0.9671	-0.76	0.0522	0.9497	-0.62	0.0864**	0.8537	-0.35	0.1255***
					h = 25							
QR(baseline)	0.9972	-0.55	0.0241	0.9888	-0.10	0.0590	0.9793	0.10	0.1072	0.9624	0.36	0.1703
QR(TVP)	0.9860	-0.71	0.0256	0.9697	-0.65	0.0533	0.9406	-0.59	0.0843***	0.9238	-0.40	0.0901***

Notes: Empirical coverage, Length and Tick Loss are computed for each quantile τ and forecast horizon h for each model considered. The horizon h is defined in number of weeks. QR(baseline) refers to the quantile regression for the standard model of [Adrian and Brunnermeier, 2016], while the QR(TVP) refers to the quantile regression with the time-varying parameters model. The Diebold-Mariano statistics refer to the hypothesis of superior predictive ability of the tick loss of each alternative model vis-à-vis the baseline quantile regression. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 1.10: Forecasting Statistics (long term)

τ	0.01			0.025			0.05			0.1		
statistic	C	L	TL	C	L	TL	C	L	TL	C	L	TL
				h = 30								
QR(baseline)	0.9944	-0.59	0.0246	0.9888	-0.15	0.0586	0.9803	0.11	0.1081	0.9641	0.42	0.1751
QR(TVP)	0.9899	-0.72	0.0245	0.9708	-0.69	0.0510***	0.9568	-0.68	0.0721***	0.9090	-0.39	0.0970***
				h = 35								
QR(baseline)	0.9949	-0.24	0.0275	0.9882	-0.04	0.0625	0.9803	0.12	0.1098	0.9657	0.49	0.1804
QR(TVP)	0.9887	-0.62	0.0269	0.9696	-0.64	0.0561*	0.9398	-0.55	0.0894***	0.9133	-0.40	0.0962***
				h = 40								
QR(baseline)	0.9977	-0.41	0.0266	0.9904	-0.06	0.0607	0.9785	0.09	0.1081	0.9605	0.50	0.1814
QR(TVP)	0.9915	-0.68	0.0254	0.9656	-0.70	0.0545	0.9492	-0.57	0.0828***	0.9176	-0.49	0.0729***

Notes: Empirical coverage, Length and Tick Loss are computed for each quantile τ and forecast horizon h for each model considered. The horizon h is defined in number of weeks. QR(baseline) refers to the quantile regression for the standard model of [Adrian and Brunnermeier, 2016], while the QR(TVP) refers to the quantile regression with the time-varying parameters model. The Diebold-Mariano statistics refer to the hypothesis of superior predictive ability of the tick loss of each alternative model vis-à-vis the baseline quantile regression. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 1.11: Forecasting Statistics - model with balance sheet data

τ	0.01			0.025			0.05			0.1		
statistic	C	L	TL	C	L	TL	C	L	TL	C	L	TL
					h = 1							
QR(baseline)	0.9754	-2.61	0.0117	0.9836	-1.37	0.0292	0.9836	-0.57	0.0585	0.9672	-0.04	0.1080
QR(TVP)	1.0000	3.02	0.0680	1.0000	1.78	0.1081	1.0000	0.96	0.1349	1.0000	0.37	0.1489
					h = 4							
QR(baseline)	0.9580	-2.86	0.0099	0.9580	-1.68	0.0247	0.9580	-0.78	0.0494	0.9580	-0.15	0.0936
QR(TVP)	1.0000	3.19	0.0701	1.0000	1.85	0.1132	1.0000	1.15	0.1459	1.0000	0.58	0.1659
					h = 8							
QR(baseline)	0.6293	-3.52	0.2149	0.6293	-2.47	0.2192	0.6207	-1.48	0.2263	0.6638	-0.75	0.1909
QR(TVP)	1.0000	3.24	0.0704***	1.0000	1.83	0.1146**	1.0000	1.86	0.1412**	0.9914	0.52	0.1627
					h = 12							
QR(baseline)	0.9640	-2.76	0.0100	0.9730	-1.87	0.0250	0.9640	-0.73	0.0500	0.9369	-0.20	0.0991
QR(TVP)	1.0000	2.99	0.0674	1.0000	1.79	0.1163	1.0000	1.25	0.1492	0.9910	0.68	0.1787

Notes: Empirical coverage, Length and Tick Loss are computed for each quantile τ and forecast horizon h for each model considered. The horizon h is defined in number of quarters. QR(baseline) refers to the quantile regression for the standard model of [Adrian and Brunnermeier, 2016], while the QR(TVP) refers to the quantile regression with the time-varying parameters model. The Diebold-Mariano statistics refer to the hypothesis of superior predictive ability of the tick loss of each alternative model vis-à-vis the baseline quantile regression. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

1.10.3 Information on the ΔCoVaR

In the original model, using conditions (1.11) and (1.12), we can compute

$$\Delta CoVaR_{q,t}^{\mathbb{S}|i} = CoVaR_{q,t}^{\mathbb{S}|i} - CoVaR_{50,t}^{\mathbb{S}|i} \tag{1.42}$$
$$= \hat{\beta}_q^{\mathbb{S}|i}(VaR_{q,t}^{i} - VaR_{50,t}^{i}) \tag{1.43}$$

The last condition gives the ΔCoVaR, which quantifies the incremental change in systemic risk when institution i is in distress relative to its median state.

And the Dynamic ΔCoVaR equivalent is given by

$$D\Delta CoVaR_{q,t}^{\mathbb{S}|i} = DCoVaR_{q,t}^{\mathbb{S}|i} - DCoVaR_{50,t}^{\mathbb{S}|i} \tag{1.44}$$
$$= \hat{\beta}_{q,t}^{\mathbb{S}|i}(DVaR_{q,t}^{i} - DVaR_{50,t}^{i}) \tag{1.45}$$

Chapter 2

Business Cycles Worldwide: The impact of the bank lending channel

2.1 Introduction

During the global financial crisis of 2007-2009, due to its unprecedented effects on the disturbance of credit supply, and the significant negative impact on the different economies around the world, many studies and papers have attempted to estimate the effects of credit supply shocks on business cycles.

Our goal is to distinguish between the contribution of the bank lending channel and the market based finance (MBF) channel to the total non-financial private sector, quantify their impact on GDP growth, and relate to different potential credit supply shocks. We also include the distinction in the borrowing channel, between household debt and non-financial firm debt, as in [Mian et al., 2017a], but with a higher number of countries in our sample, as well as additional potential instruments. We consider these 4 different channels (the 2 segments of the borrowing sector and the 2 segments of the lending sector), and classify them as our 4 credit/debt variables considered in our study. We debate the main source of these effects, and focus on either credit demand or credit supply shocks, in addition to other alternatives.

To do so, we resort to a country-level unbalanced panel dataset, with 136 different countries, between 1960 and 2021, with an annual frequency. We focus on the impact that a 3-year change on each of the 4 credit/debt variables (between t-4 and t-1) can have on a 3-year change in subsequent GDP growth (between t and t+3). As for the source of these effects, we consider 6 different instrumental variables: the real sovereign spread (spr^{real}), the mortgage sovereign spread (spr^{MS}), the corporate credit spreads (spr^{corp}), the Excess Bond Premium (EBP), the Financial Conditions Index (FCI), and the Principal Component (PCA), which is a combination of all 5 previous instruments. In terms of robustness to our results, we provide different alternative scenarios, consisting of interactions with the public sector and government accounts, with the external sector, different sets of country and period fixed effects, subsamples, forecasts, and others.

We start by showing a systematic empirical relation between the 4 different credit/debt variables and business cycles, and the higher significance of either bank credit or household debt in explaining changes in subsequent GDP growth. During the bank credit or household debt booming periods, the consumption to GDP ratio rises, and there is a boost to GDP. But this is only temporary, as subsequent GDP experiences a fall. Thus, an increase in either bank credit or household debt to GDP ratio for a three-year period in a specific country leads to a decrease in future GDP growth.

This effect is, not only, statistically significant across different scenarios, but also large in terms of its magnitude. When considering our whole sample, a one standard deviation increase in bank credit to GDP ratio over the previous 3 years (2.0 percentage points) leads to a 1.2 percentage point decline in GDP in the next 3 following years. For household debt, a one standard deviation increase over the previous 3 years (2.8 percentage points) leads to a 1.1 percentage point decline in GDP in the next 3 following years. This predictive[1] relation is robust across different subsamples, restricting either the number of periods, the number of countries, or other elements. Excluding the period of the Great Financial Crisis, by only considering the years in our sample until 2006, has little effect in our results. The bank credit coefficient is reduced by 23%, and the household debt coefficient is reduced only by 6%, while both retain their statistical significance at the 1% level. For the other remaining components, non-financial firm debt (on the borrowing side) and market based finance (MBF, on the lending side), the effect seems to be the opposite: there is an initial negative impact on GDP growth, which is then, reversed towards a positive effect in subsequent periods. However, even though we can verify this pattern, it is not always consistent throughout the different scenarios, nor does it retain its statistical significance. Thus, their dynamics do not generate an opposite boom-bust growth cycle effect that we are able to identify in the bank credit and household finance.

We, then, try to relate our findings with different economic models which are also consistent with empirical data. We focus on 2 main categories: credit demand shocks and credit supply shocks. Considering both these categories, we allow for interactions with rational expectations, macroeconomic frictions, behavioural models, and additional components. Our results, combined with empirical evidence, point to models with credit supply shocks, while models with credit demand shocks would lead to counterfactual results. They also reflect the relevant impact of macroeconomic frictions, and the relevance of lenders' and investors' behavioural biases.

More specifically, in models with credit demand shocks and rational expectations, the corresponding shock is either related to an increase in current or future productivity, or an increase in permanent income which households use as basis for higher borrowing, with the goal to smooth

[1]We follow standard time-series econometrics terminology when we apply the term "predict", which refers to the predicted value of an outcome using the entire sample to estimate the regression. This is in contrast to the term "forecast" that refers to the estimated value of the outcome variable for an observation that is not in the sample used to estimate the regression coefficients. This definition is in accordance with [Stock and Watson, 2011], chapter 14.

consumption over the life cycle. However, in these cases, there would be a positive impact of current changes in credit/debt on future GDP growth. But as we have explained before, the correlation we found between these two variables is negative. In addition, our findings do not match with credit demand models in which the shock is related to borrowers' beliefs. Higher optimism by borrowers and a fixed credit supply results in higher interest rate spreads charged by the lenders, since there is an increase in the amount borrowed, but no changes in the fundamentals. But when we consider different interest rate spreads in our sample, we get the opposite conclusion: higher bank credit or household debt is associated with low interest rate spreads. Instead, a decrease in the interest rate spreads charged by lenders and investors, combined with high credit/debt would fit better with models based on credit supply shocks.

Thus, our results fit into models in which a credit supply shock leads to an increase in bank credit or household debt, which, itself, leads to lower future economic growth. The following question would be regarding the source of the credit supply shock. In most models with credit market sentiment, it relates to a change in the beliefs of lenders and investors, associated with an underestimation of downside risks during booming periods, increasing the willingness to boost the amount of credit lent, or to cut the costs associated with borrowing (more detail on these models is provided in the Literature review section). Although we do not have certain evidence of this, we use a potential proxy for lenders' and investors' beliefs, based on the economic forecasts of the IMF and OECD, which consistently overestimate future GDP growth during (and shortly after) bank credit or household debt booming periods. Given that the build-up of household debt or bank credit in the previous three years is known by forecasters at the time when they make their predictions, any difference between these predictions and the actual values would consist of forecasting errors. This is consistent with many areas of research pointing to negative effects of more aggressive lending by the financial sector not being incorporated by market participants (for example, [Baron and Xiong, 2017] or [Fahlenbrach et al., 2018]).

The results also manifest the importance of monetary policy constraints and nominal frictions, which reinforce the negative impact of the bank credit and household debt on future economic growth[2]. For example, the negative impact of bank credit on future economic growth is higher within fixed exchange rate regimes than under floating exchange rate regimes. Both household debt and bank credit have an increasing effect on unemployment, and their relationship with GDP growth is non-linear, consistent with downward rigidity in wages and interest rates: an increase of household debt or bank credit leads to a lower GDP growth, but the opposite effect does not verify. That is, lower bank credit or household debt does not lead to an increase in future economic growth.

We end with a comparative analysis between the country specific credit/debt cycles and the corresponding global cycles. The subsequent net exports is also negatively influenced by current

[2]This is consistent with the literature, including [Eggertsson and Krugman, 2012], [Korinek and Simsek, 2016], and others. More detail is provided in the Literature review section.

rises in credit bank or household debt, pointing to potential spillover effects on other countries. Although, this could turn out beneficial, as economies that are more open to foreign trade see an actual positive effect on net exports, which might minimize or even counterbalance the negative direct effects on GDP growth. However, this depends on the correlation between specific cycles with the global cycles, as we find that higher correlation between the 2 leads to stronger negative impacts on subsequent GDP growth. This is expected, as specific countries will have a lower margin to benefit from an increase in net exports, when the majority of foreign countries are also dealing with the negative effects of higher bank credit or household debt at the same time.

Overall, we find similarities between the impact of bank credit and household debt, which would point to a connection between the 2 segments. When comparing the 2 segments of the borrowing sector, household debt and non-financial firm debt, and how they would differ in terms of resorting to the 2 different segments of lending (either bank credit or market based finance (MBF)), one would expect that households would recur more to bank lending than market based finance, on a proportional basis, when compared to non-financial firms. But we additionally find some differences in terms of statistical significance and magnitude in the different scenarios, where the bank credit shows more robustness to different specifications than the household debt. This would imply that there is a significance of the bank credit that goes well beyond the household debt. It would also mean that the main component that generates the boom bust cycle in GDP would be the bank credit, independent of its destination, rather than household debt, independent of its financing. Thus, some caution would be advised on assuming such a connection.

The structure of the paper is as follows. Section 2.2 reviews the relevant literature related to our topic. Section 2.3 outlines the Data used throughout this study, as well as a summary of the main statistics. Section 2.4 describes our initial methodology and results. Section 2.5 highlights the changes to this methodology, adopting Instrumental Variable (IV) regressions, and provides a description of the instruments used and corresponding results. Section 2.6 presents our evaluation of how rational or biased expectations impact our findings. Section 2.7 discusses the role of macroeconomic frictions. Section 2.8 considers the influence of house prices and other predictors of GDP growth. Section 2.9 compares the country-specific credit/debt cycles with the global counterparts. Section 2.10 provides the conclusions of this paper.

2.2 Literature review

2.2.1 Main paper

Our paper is related to [Mian et al., 2017a], who focus on the different impact of household credit, on one hand, and the non-financial firm credit, on the other hand, on GDP growth. The authors separate these 2 components of the total private non-financial borrowing sector, and find that household debt as an initial positive impact on GDP growth (in the current year), while reverting to a negative impact in the subsequent 2 to 5 years. The non-financial firm debt exerts the opposite effect: the initial impacts are negative (in the current and up to the 3 following years), but turn positive in the last 4 and 5 years. Nevertheless, the authors point to different tests to find that, while household debt maintains its statistical significance in different scenarios, non-financial firm debt does not. They resort to a panel data model and a VAR (Vector AutoRegressive) model, composed of 30 countries from 1960 until 2012, and find that an expansion in household debt leads to a lower GDP growth and higher unemployment. Using mortgage spreads as an instrument, they find that low mortgage spreads are correlated with higher household debt and lower future GDP growth, pointing to the relevance of credit supply shocks. Our research differs from this paper by shifting the focus from the borrowing sector to the lending sector, more specifically, the different impact between bank lending and market based finance (MBF) to the private non-financial sector. We also increased the total number of countries in our sample to 136 (subjected to availability of the data for the different variables).

2.2.2 Initial work

Initial literature on the role of credit and debt markets focused more on the propagating or transmission mechanism (with potential amplifying effects), rather than a possible source of a shock. According to [Boivin et al., 2010], the source would be on monetary policy, and the transmission to the real economy occurs through either borrowers (households or firms), or the balance sheet of banks or financial intermediaries. Most of these papers would employ a DSGE (Dynamic Stochastic General Equilibrium) model to evaluate this transmission effect, including [Kiyotaki and Moore, 1997], with collateral constraints on borrowing, and [Bernanke et al., 1999], with connections between the external financial premium, and the net worth of borrowers, giving rise to the "financial accelerator" amplification mechanism.

Later studies considered the possibility that, indeed, credit could be seen as a trigger of business cycles, and incorporated banking or financial sectors in the previous DSGE models. This would include credit spread shocks in [Curdia and Woodford, 2010], bank valuation shocks in [Gertler and Kiyotaki, 2015] and the "risk shocks" in [Christiano et al., 2014], allowing volatility of cross-sectional idiosyncratic uncertainty to change over time.

2.2.3 Origins of shocks

There is extensive literature on credit supply shocks. This would imply either changes in the cost of credit, or in the amount willing to lend. We begin with the potential sources of the credit supply shocks. [Peydró, 2014] explain that the different possibilities can be grouped in 2 main channels: the preference channel and the agency channel. Most models seem to fit into the preference channel, including [Minsky, 2008], [Gennaioli et al., 2012], [Landvoigt, 2016], and [Greenwood et al., 2016]. They point to lender sentiment and prediction errors as a possible cause, where either higher amounts of credit, or credit at a lower cost, are provided by the lending agents in the model, resulting from their undervaluation of negative risks during credit booms. In fact, [Greenwood and Hanson, 2013], and [Fahlenbrach et al., 2018] provide empirical evidence that, indeed, the economic intervenients are not able to incorporate the negative consequences of aggressive lending by the financial sector in their decision making process. There are also empirical studies that show a predictable reversal in the sentiment of the lenders. [Baron and Xiong, 2017] find that credit expansions in the private sector leads to an increase in bank equity crash risk, with a sample of 20 developed countries between 1920 and 20212. [Bordalo et al., 2018] show that lenders are vulnerable to errors in the construction of their expectations. More specifically, during boom periods, they only incorporate recent periods and information, which is biased towards low spreads and underestimate possible risks, including tail risk. Habit formation models could also be included in this category, as in [Campbell and Cochrane, 1999], which capture changes in the risk appetite of agents in the economy in accordance with the business cycle. We take this possibility into account by considering the impact of IMF and OECD forecasts, for different horizons, as well as forecast errors.

The agency channel would point to limited liability and excessive leverage, leading to higher risk appetite from financial intermediaries, as the potential source. These would include influxes of foreign capital into domestic markets, as in [Favilukis et al., 2017], which leads to relaxation of collateral constraints on borrowing. Or deregulations, or more efficient lending technologies/techniques, as in [Justiniano et al., 2015]. Or monetary policy by core countries (including [Bruno and Shin, 2015], [Miranda-Agrippino and Rey, 2015], and [Rey, 2015]).

2.2.4 Demand vs Supply

Shocks to credit demand have also been considered. There are no changes to lending standards, borrowers simply increase the amount they want to borrow, or there are more agents willing to borrow in the economy. [Aguiar and Gopinath, 2007] connect this increase in current credit to expectations of higher future income. These expectations will imply an increase in the consumption possibilities, and credit is used to smooth that increase in consumption throughout different periods. The possible causes of these increases in expectations are numerous, ranging from technology shocks, to shocks on trading conditions. Other possibilities would be liquidity constraints, where credit demand increases in order to preserve liquidity, and more easily smooth consumption in the face of a negative shock. But this would imply that higher credit growth would not result in more consumption (but would yield a rise in savings instead). This conflicts with empirical evidence, as well as our own results, in which we witness an increase in consumption during credit booms. One final option would be behavioural explanations, or changes in the preferences of the agents (usually the households), resulting in higher consumption (for example, [Laibson, 1997]), or positive changes in expectations (as in [Barro, 1999] and [Brunnermeier and Parker, 2005]). In this case, consumption would increase with the expectations, and subsequent economic growth would decrease either due to a reversal of the expectations, or due to less productive investment.

In addition to considering credit demand as the possible source of the shock, instead of credit supply, we also need to consider that it may be difficult to disentangle each other, and that it is likely that they even reinforce one another. However, one of the major flaws in credit demand models was identified by [Justiniano et al., 2015], in which they argue that the credit demand shocks lead to higher interest rates during the boom period, in all of these different models. However, this is a counterfactual result to what happened during the 2007 household debt crisis in the United States. [Mian et al., 2017b] also find evidence against the credit demand channel hypothesis. More specifically, they find that an increase in household credit due to higher household income (which would fit into the credit demand shock possibilities) does not result in an increase in GDP growth. Instead, they find that higher household credit is associated with low spreads between mortgage and sovereign debt, pointing to credit supply shocks. Finally, [Krishnamurthy and Muir, 2017] find empirical evidence that spreads between bonds with high and low risk fall before financial crisis, in a sample of 19 countries. All these elements point to the credit supply being the main source of the credit increase that leads to economic volatility.

2.2.5 GDP Impact

We also find a negative impact of credit increase on GDP growth, in the subsequent periods to the credit rise. Several factors have been put forward to explain this phenomenon. The first one is nominal rigidities. For example, [Schmitt-Grohé and Uribe, 2016] incorporate wage rigidity and monetary policy constraints (for example, on exchange rates) in their model, removing tools for the economy to adapt to the shock (for example, with a decrease in real wages in the face of a downward credit supply shock. Instead, the adjustment would have to be through a decrease in employment and GDP). We also consider this aspect through the influence of different exchange rate regimes. Another factor is connected to disturbances in the financial sector, as in [Krishnamurthy and Muir, 2017] and [López-Salido et al., 2017]. Others include the combination of borrowing constraints and short-sighted consumers, as in [Eggertsson and Krugman, 2012], [Guerrieri and Lorenzoni, 2011], [Farhi and Werning, 2016], [Philippe and Philippon, 2017] and [Korinek and Simsek, 2016]. In these papers, the economy enters a zero lower bound constraint, which renders the monetary policy unable to lower the interest rates, and pushing the adjustment through a negative impact on the economy. The build-up of the boom occurs because impatient consumers are not able to incorporate these developments, and will contract excessive credit. A final element focuses more on non-financial firms, and how excessive credit of these agents can generate fire sales externalities, present in [Shleifer and Vishny, 1992], [Kiyotaki and Moore, 1997], [Lorenzoni, 2008], and [Dávila, 2015].

Not only does credit growth influence GDP, but it has also been identified (along with rise in leverage) as a powerful predictor of incoming financial crises. [Reinhart and Rogoff, 2009] show that ascending external debt may lead to banking crises and even sovereign debt crises. [Jordà et al., 2011] also focus on external imbalances, documenting foreign liquidity inflows, expansionary monetary policy and changes in financial technology as the root causes. The reasoning is that this initially leads to higher wealth and deposits, but that increase is limited, shifting to higher credit. However, [Gorton and Ordoñez, 2019] explain that not all credit booms are nefarious for the economy. They provide a distinction between bad booms (those that end in crisis) and good booms (those that do not), and try to connect them to productivity growth, defining it as the triggering element. In the case of bad boom, the positive productivity shock ends quicker when compared to the good boom. [Jorda et al., 2012] resort to a panel data sample of 140 years and 14 countries, and identify 200 different recessions. They show that recessions are more costly if preceded by a financial crisis, and credit booms are more likely after significant recessions and costly recoveries. [Taylor and Jordà, 2016] attributes this to a higher leverage and the rising financialization of the economy in developed countries in the last 40 years. [Gourinchas and Obstfeld, 2012] use a sample of 79 emerging economies instead, and put forth 3 main predictors of financial crisis: higher credit, increasing leverage, and real currency appreciation. They also explain that the conclusions hold for developed countries as well.

Our results also indicate a lower impact of non-financial firm debt on GDP growth, than household debt, which is also the case in [Mian et al., 2017a]. [Jappelli and Pagano, 1994] explain why household credit may exert a higher impact on GDP growth than firm credit. They explain that an expansion in household credit due to lowering of credit costs also has a decreasing effect on savings. This will lower firms' capital accumulation, and lead to lower levels of investment, productivity and GDP growth. [Erel et al., 2012] put forth an additional factor: that large firms' (which account for a significant portion of the firm sector) credit behaviour is countercyclical. That is, they smooth their revenues and borrow more significantly during recessions, easing the recessive impact on GDP growth. [Gross and Souleles, 2002] and [Agarwal et al., 2015] point to differences in behavioural bias between these 2 agents. It is very likely that firm's representatives have more capabilities to properly assess relevant information on future revenues and credit costs, when compared to households, who are more vulnerable to short-sightedness and positive bias of credit conditions and future income. Lastly, [Mian et al., 2017a] also consider higher regulations, requirements and debt-restructuring laws (like bankruptcy laws) applied to firms, that help minimizing the accumulation of credit, as well as the negative impact on GDP. On the other hand, regulations and limitations for household credit are more limited, as well as debt-restructuring legislation.

2.2.6 Propagation channels

Focusing on the relation between credit supply shocks and house prices, papers including [Landvoigt et al., 2015], [Favara and Imbs, 2015], and [Adelino et al., 2014], provide empirical evidence for the effect of credit supply shocks on house price movements, which we also consider here. [Jordà et al., 2016] point to the connection between household debt and house prices, where the main destination of household credit is related to mortgage credit. This will increase volatility in house prices, and leave households vulnerable to significant decreases in house prices, since these are used as collateral. [Mian et al., 2013] find some empirical evidence in this direction, where consumers are highly exposed to shocks on house valuation. [Favilukis et al., 2017], [Justiniano et al., 2015], and [Landvoigt, 2016], consider different models where changes in the lending sector exert spillover effects on house prices, which is also a component we are interested in.

Our focus on the importance of the credit for the non-financial private sector of the economy is also present in [Jorda et al., 2015], [Schularick and Taylor, 2012], [Jordà et al., 2013], [Jordà et al., 2016], [Reinhart and Rogoff, 2009], and [Dell'Ariccia et al., 2012]. They resort to a long run historical data for developed economies, and find that credit growth works as a good predictor of financial crisis (where house credit growth seems to be the most relevant one). And the larger the credit growth, the larger the negative impact on GDP. Others, including [Charles et al., 2018], [Borio et al., 2016], and [Gopinath et al., 2017] go even further, pointing to a negative impact of credit booms on capital accumulation, which reduced even long run GDP. Although other authors, like [Cecchetti et al., 2011], do not find that the level of private debt impacts GDP growth, this could be simply explained by using the level of debt, instead of the growth of debt. As a result, we use debt growth instead of debt level for the different variables in the model.

Many authors study the "investment" channel to understand business cycle dynamics, including [Bernanke and Gertler, 1989], [Kiyotaki and Moore, 1997], [Caballero and Krishnamurthy, 2003], [Brunnermeier and Sannikov, 2014], and [Lorenzoni, 2008]. Although we consider the non-financial firm credit side of the borrowing channel, which could be seen as a proxy for the investment side of borrowing, the main focus is on the lending channel, independent of the final destination of the credit funds.

Others find more relevance in the financial sector. It is likely that structural and significant changes in the credit markets would alter the impact of credit supply shocks in the rest of the economy, for example, connected to financial liberalization in the recent decades, which pushed for more competition and increased financial globalization. This point is provided by [Peydró, 2014], who offers a literature review on this topic. [Adrian and Shin, 2009] point to a specific component of financial innovation: securitization. Securitization consists of pooling or merging different financial assets (usually illiquid assets) into a single asset (more easily marketable), propping up credit supply. On the other hand, it also led to the expansion of the shadow banking system. [Boivin et al., 2010] highlight 2 main impacts from this expansion of the shadow banking system resulting from securitization: 1 - Additional financial opportunities for investors and borrowers; 2 - easier and faster access to credit. Also, [Cecchetti and Kharroubi, 2019] find significant correlation between the growth in the financial sector and the decrease of GDP growth. This seems to be in accordance with our findings, where the bank lending channel is the main channel that impacts GDP growth, even though the amount of credit is similar, on average, to the market based finance (MBF) lending channel. Also, the impact on GDP growth is initially positive, but turns to be negative in the subsequent years.

2.2.7 VAR models

An alternative methodology to panel data models that is commonly used for credit supply shocks is the VAR (Vector AutoRegressive) models. [Mian et al., 2017a] apply both methodologies in their paper. In the VAR model, they identify the structural shocks through Cholesky decomposition, and explain the goal is not to identify causality, but to describe the full dynamic relation between GDP growth and the 2 borrowing sectors (household debt and non-financial firm debt). They perform different tests, and find that the behaviour of the impulse responses is not sensitive to the ordering of these 3 variables in the VAR model. They also state that the VAR estimates are only slightly different from the OLS estimates in the panel data model.

[Eickmeier and Ng, 2015] employ a GVAR (Global Vector AutoRegressive) model, with a dataset composed of 33 countries, from 1983 to 2009, to infer on how US credit supply shocks are transmitted to other economies. In order to connect the US with other countries, they use bilateral trade, portfolio investment, FDI (foreign direct investment), and banking exposures. To identify the credit supply shocks, they resort to sign restrictions. Sign restrictions work in the following manner: a negative credit supply shock either decreases in the same period or has no effect on GDP or the amount of credit. The negative impact is restricted to be higher for credit amount than GDP (that is, in the face of a negative credit supply shock, the amount of credit has to decrease by more than GDP). On the other hand, the effect on corporate bond rate, the spread between corporate bond and long-term government bond rates, and the spread corporate bond and short-term interest rates is restricted to either increase or having no effect. They find that the negative US credit supply shocks have a statistically significant negative impact on the GDP of the US and the other countries as well, as they explain about 20% of one-year-ahead of the GDP FEV (forecast error variance) in the US, 10% of one-year-ahead of the GDP FEV (forecast error variance) in the Euro Area and the United Kingdom, and lower values for all the remaining countries in the sample.

[Gambetti and Musso, 2017] incorporate a time-varying component and stochastic volatility into their VAR model, and use loan level data to the non-financial private sector in US, Euro Area and the UK, between 1980 and 2011, also using sign restrictions as the identification strategy. More specifically, they restrict the loan supply shock to have a positive effect on real GDP, inflation, loan amount and short-run interest rate, and have a negative effect on the lending rate. They show that these shocks have a significant effect in all 3 regions, especially during recessions and in more recent years.

[Mumtaz et al., 2018] use different sVAR (structural Vector AutoRegressive) models, and through a Monte Carlo experiment, show that the performance of the different models varies significantly. Applying the best performing models to the US economy, with 5 variables (GDP growth, CPI (consumer price Index) inflation, lending changes to households and non-financial firms, spread and three-month Treasury Bill) they find that these shocks account for around 50% of the decline in GDP growth during the Great Financial Crisis. [Barauskaitė et al., 2022] resort to a Bayesian VAR model, also using sign and inequality restrictions for the identification of the 2 different shocks in the lending sector.

2.2.8 Bank lending vs Market based finance (MBF)

We focus on the potential different impact of the bank lending channel vs the market based finance (MBF) channel on GDP growth. Recent work by [Barauskaitė et al., 2022] also reflects interest in this difference. In their case, they resort to a Bayesian VAR model, using inequality restrictions to distinguish between the shocks to the 2 sectors, and focus on credit to non-financial firms, in the euro area as a whole and in its five largest countries. To distinguish between the 2 lending sectors, they use either activity-based measures (loans vs debt securities), or entity-based measures (bank vs non-bank debt financing). They resort to a new quarterly dataset of loan and market based finance data for Euro Area non-financial firms, which includes financing data from within the Euro Area and around the world. To conduct the analysis at a country level, the loan level data is then compiled into the 5 largest Euro Area countries. They find that both channels are relevant in explaining GDP growth and business cycles, and that there is heterogeneity in which of these is more relevant. In our case, it is the bank lending channel that seems to exert the more significant influence on GDP growth. However, when we restrict our sample to the same countries used in this paper, indeed, we find that there is an increase in the significance of the market based finance (MBF) lending channel, that is, there are more scenarios where the market based finance (MBF) is statistically significant. However, the bank lending channel still remains the more significant channel in most of the scenarios.

Thus, we can conclude that it is likely that the relevance of the lending channel (whether banking or market based finance (MBF)) is heterogeneous, as the authors found in their smaller sample. In their case, they find that, for Germany and France, the market based finance (MBF) is more relevant than the bank lending channel, where the opposite was true for the 3 remaining countries. In our sample, this also seems to be the case. When we include all the 136 countries, it seems we have more countries for which the bank lending channel is more relevant. Still, since the bank lending channel remains statistically more relevant than the market based finance (MBF) in a similar sample, there are some differences with the results obtained in this paper. A possible explanation would be the consideration of the whole private non-financial borrowing sector (household debt + non-financial firm debt), whereas this paper only considers the non-financial firm sector for borrowing. If we considered what the results likely would be if we removed the household credit from our sample, we would argue that it would increase the relevance of the market based finance (MBF). The reasoning is simple: households are more likely to resort to bank lending than to market based finance (MBF), when compared to non-financial firms.

Nevertheless, other elements would have to be considered for the possibility of different results, including differences in the methodology, and/or the data used for the estimation. In terms of the data, we resort to the Bank for International Settlement's (BIS) "Long series on total credit to the non-financial sectors" database. One of the potential flaws is that, for earlier years, it may not include off-balance-sheet securitized lending or credit by non-bank financial institutions. Although this would be for just a few observations, it could constitute a possible difference in the results. This issue is discussed in more detail in the Data and Summary Statistics section. Regarding the methodology, as we explained before, [Mian et al., 2017a] apply both a VAR and OLS methodologies, and find that the VAR estimates are only slight different from the OLS estimates in the panel data model, in the case of the borrowing sector. It is possible that this also verifies for the lending sector. Nevertheless, this remains to be tested in future work.

[Aldasoro and Unger, 2017] point to the rising proportion of non-bank lending and market based finance in the Euro Area. They resort to a VAR model to compare lending from bank loans and lending from all other sources (equity, debt securities and non-bank institutions), to the whole non-financial private sector in the Euro Area (non-financial private firms, households and non-profit organizations connected to households). They use loan level data, and distinguish between the 2 types of credit supply shocks (bank vs other external financing) through the substitution between the 2 possibilities. That is, when a negative shock affects bank loan supply, it will lead to lower bank lending and higher lending from other financing sources.

There is extensive research that mainly focuses on the bank lending channel. [Alfaro et al., 2021], for example, use bank-firm-loan level data from the Spanish economy for corporate loans between 2003 and 2013, with the goal of estimating firm-specific credit supply shocks for each year. They find considerable direct propagation effects through firms' suppliers (but not through customers) on unemployment, investment and GDP, especially during the Great Financial crisis. [Amiti and Weinstein, 2018] apply a similar methodology to a sample of 150 banks and 1600 firms in the Japanese economy, between 1990 and 2010, to estimate the impact of credit supply on firms' investment, and use differences in credit growth between bank's lending to the same firms. They find that bank supply shocks explain 30% to 40% of the changes in overall loans and investment. [Demir et al., 2022] show that liquidity-constrained firms spread the negative consequences on the cost of imports to the consumers. [Giannetti and Saidi, 2019] discuss insights on how the structure of the bank system and the share of lenders on the loans in a specific sector may affect the spillover of credit market shocks to the rest of the economy. [Costello, 2020] present evidence that firms that are more reliant and dependent on bank lending propagate the negative effects of a decline in credit to their consumers. This results from 2 effects: 1 - decrease in the credit offered by the lenders; 2 - lower production and supply of goods and services. [Bentolila et al., 2018] create 2 subsamples, differentiating between vulnerable and healthy banks. The separation criteria used was the banks that were bailed out during the Great Financial Crisis. They show that these banks decrease their credit supply significantly before the bailout, and that 24% of the job losses at these firms are due to their exposure to the weak banks. [Chen et al., 2017] explain that lending to small businesses by large banks has decreased significantly in 2008 and remain low through 2014, and treat this as a credit supply shock. The results show a decrease of the amount of credit lent to these firms, higher interest rates, higher unemployment, and lower wages between 2006 and 2010. As other lenders substituted the large banks after 2010, interest rates remained high, and wages remained at their lower level.

2.2.9 Instrumental variables

Like in any model using instrumental variables, it is rather difficult to guarantee the exogeneity condition of the instrument. Therefore, we employ different instruments in our model to identify credit supply shocks. We resort to corporate credit spreads, which have been employed by [Gilchrist and Zakrajsek, 2012] and [Krishnamurthy and Muir, 2017]. We also resort to mortgage sovereign spreads, which has been used by [Mian et al., 2017a]. The importance of credit spreads have been highlighted in [Krishnamurthy and Muir, 2017], for example, who show that credit spreads fall and are excessively low before a crisis, and the trigger of the crisis comes from a large and unexpected increase in those same spreads. [López-Salido et al., 2017] show the predictability of a significant reversal of low credit spreads, using US data between 1929 and 2013. Nevertheless, there are always doubts and questions on how accurate the instruments are. For example, [Nevo and Rosen, 2012] point to mortgage sovereign spreads being an "imperfect instrumental variable". According to the authors, the estimates can be upward biased by neglecting credit demand shocks, due to the positive relation between increase in credit on future GDP growth, resulting from anticipated increases in future income. However, as in [Mian et al., 2017a], we obtain a negative impact of mortgage sovereign spread on subsequent economic growth, and given that the omitted variables would push for the upward effect, we can state that our estimates are conservative, when quantifying the negative effect of credit supply shocks on economic growth.

Another instrument that we included was sovereign spreads (relative to the US Treasuries), focused on European countries, in the years after the introduction of the single currency and leading up to the financial crisis. According to [Mian et al., 2017a], the introduction of the single currency led to lower risk premia, especially currency risk, leading to a convergence between sovereign spreads. As countries in the peripheral area had higher spreads than countries in the Eurozone core before the single currency, this led to a comparative improvement in the credit conditions provided in peripheral countries, and a corresponding increase in their credit supply. [Remolona et al., 2007] and [Longstaff et al., 2011] explain that changes in the risk premia are the main cause of changes in the sovereign yield spread. This is also backed up by [Bofondi et al., 2018], who provide empirical evidence, focused on European Union countries, that changes in the sovereign spread have an independent effect on the domestic credit supply to non-financial agents (mainly firms and households). Nevertheless, [Charles et al., 2018], [Borio et al., 2016], and [Gopinath et al., 2017] point to potential drawbacks on the usage of this instrument. More specifically, that the negative influence on output may be related to the destination of credit (for example, large household debt expansion, on one hand, or allocated to unproductive firms, on the other hand), and not exactly due to the simple increase of the credit supply, or due to the specific lending channel. Hence, we use 4 variables through which the instrument may work through, which are the 2 borrowing channels (the mortgage credit and the non-financial firm credit), and the 2 lending channels (the bank credit channel and the market based finance (MBF) channel).

We also resort to the EBP (Excess Bond Premium) as a possible instrument. According to [Gilchrist and Zakrajsek, 2012], it comprises the component of credit spreads that is orthogonal (that is, statistically independent) to default risk. In their case, this is applied in a framework of a SVAR (Structural Vector AutoRegressive) model, where the shock to this instrument is considered as a credit supply shock, identified through a recursive scheme. Other papers use it in a similar manner, although some resort to a time-invariant SVAR, including [Lown and Morgan, 2006]. [Bleaney et al., 2016] resort to this measure to exploit the cross-section dimension, that is, to compare the possible different responses to the bond spread measures in eight European countries, which could be explained by the differences in the depths of capital markets across these countries. Indeed, they find that the estimated coefficients for the EBP are different across the countries in the sample, or even Euro Area countries. When, instead, they focus on even smaller subsets (for example, Germany, France and The Netherlands), they find they are similar. They also remove the distorting elements (including default risk and bond characteristics) in order to enhance the predictive capabilities of the EBP, outperforming models that omit bond spreads, and more parsimonious models, like standard Random Walks or autoregressive models. [Mumtaz et al., 2018] lay out a list of 5 proxies for credit supply shocks that have been proposed in empirical literature: 1 - The first one is the EBP (Excess Bond Premium) that we just explained; 2 - the measure of bank lending shocks (BCDZ), provided in [Bassett et al., 2014]; 3 - innovations to the financial condition index, calculated by [Jermann and Quadrini, 2012]; 4 - the risk shock, explained in the DSGE (Dynamic Stochastic General Equilibrium) model of [Christiano et al., 2014]; 5 - a textual measure to estimate changes in uncertainty (which consists on identifying specific words that appear, including "credit crunch", or "tight credit", in media or news sources), in a similar way to [Baker et al., 2016]. In our paper, we have not included the other additional measures on the list, due to their unavailability for a significant number of countries in our sample (although we also consider a similar financial condition index measure, which we will explain in more detail below).

Other instruments that convey the quality of credit, rather than the quantity of credit, have also been used. The intuition is that the lower credit quality borrowers may be a better predictor than a decrease in interest rates. [Greenwood and Hanson, 2013] put forth the argument that the share of risky firm borrowing is preferable to measure credit market conditions, instead of interest rates on corporate credit. They provide empirical evidence for firms in the US between 1962 and 2008. [Mian et al., 2017a] use a similar measure, but applied to household credit. [Ben-Rephael et al., 2021] go even further, and find that higher investor demand for riskier assets will push for more lending to riskier borrowers, by relating the shift of mutual funds towards riskier bonds to an increase in the [Greenwood and Hanson, 2013] measure. [Di Maggio and Kermani, 2017] resort to the enactment of anti-predatory-lending laws in 2004 to verify if an increase of the credit supply to riskier borrowers led to the boom and bust cycle in house prices and lower GDP during the Great Financial Crisis. They find that, in the pre-crisis period of 2004-2006, it led to a significant increase in the lending, and a moderate increase of GDP and employment, which reverted and turned negative in the following years.

2.3 Data and Summary Statistics

2.3.1 Data

Our sample comprises of country-level unbalanced (with missing values) panel dataset, composed of 136 countries, between 1960 and 2021, at an annual frequency. A more detailed list of variables that we use in the model, and the source of the data is provided in Appendix 2.11.1.

We define the amount of household debt/credit and non-financial firm debt/credit as the household credit to GDP ratio and non-financial firm credit to GDP ratio. We use the same reasoning for the lending channel, and define the amount of bank credit and the market based finance (MBF) as the bank credit to GDP ratio, and the market based finance to GDP ratio. These variables are classified as $c_{it}^{H} = \frac{D_{it}^{H}}{Y_{it}}$, $c_{it}^{NF} = \frac{D_{it}^{NF}}{Y_{it}}$, $c_{it}^{B} = \frac{C_{it}^{B}}{Y_{it}}$, and $c_{it}^{MBF} = \frac{C_{it}^{MBF}}{Y_{it}}$, respectively. Likewise, we measure the change in household, non-financial firm, bank and market based finance (MBF) from year t-k to year t as $\Delta_k c_{it}^{H}$, $\Delta_k c_{it}^{NF}$, $\Delta_k c_{it}^{B}$, and $\Delta_k c_{it}^{MBF}$. These debt and credit measures, D_{it}^{H}, D_{it}^{NF}, D_{it}^{B}, and D_{it}^{MBF} are defined as the outstanding levels of credit to households and non-financial corporations, for the first 2 measures, and the credit from banks and all remaining sources to the entire private non-financial sector, for the remaining 2 measures. All of them are from the Bank for International Settlement's (BIS) "Long series on total credit to the non-financial sectors" database[3]. The BIS credit data is intended to capture total credit to households, non-profit institutions serving households and non-financial corporations (both private-owned and public-owned) in the economy. Credit is defined as loans and debt securities (bonds and short-term paper), and is provided by domestic banks, all other sectors in the economy and non-residents. If we compare with the definitions provided in [Schularick and Taylor, 2012] or [Jorda et al., 2015], who focus on bank lending, this definition encompasses more scenarios, but also allows to incorporate more information, and contains a richer dataset for many of the countries in our sample. The credit data is provided on a quarterly level, and captures the outstanding amount of credit at the end of each quarter.

As explained by [Dembiermont et al., 2013], in order to contain as many periods and observations as possible, this dataset is compiled from different sources, but reasonably comparable across different countries, which include the financial accounts of institutional sectors (non-financial corporations, general government, households , and non-profit institutions serving households), balance sheet data of domestic banks and non-bank financial institutions, and international banking statistics. The main source of the data is the financial accounts, but when this is not available, the other elements are used as a proxy for the total credit amount. The financial accounts data is prioritized, since the other sources usually do not include off-balance-sheet securitized lending or credit by non-bank financial institutions[4]. We use the break-adjusted

[3]The data is available for 41 countries in our sample. The total sample of the BIS series is composed of 44 countries.

[4]This is more frequent in earlier years in the data, even more so for longer series. Since we are also interested in the lending of the non-bank sector, which includes non-bank financial sector, these periods will miss some of

series provided by the BIS, to take into account any changes in the underlying data source, in the measurement used, and the coverage induce breaks in the series.

2.3.2 Summary Statistics

We begin with the analysis of the information provided in Table 2.25 in the appendix. The table contains the list of the main countries in our sample (41 out of the 136), as well as the mean and the standard deviation of household debt, non-financial firm debt, bank credit and market based finance (MBF). As we can see, there is a lot of heterogeneity, in terms of the borrowing sector, as well as the lending sector, across the different countries. We have countries in which most of the borrowed resources are allocated to the non-financial firm sector (for example, Sweden, or Luxembourg), while others allocate more to the household sector (for example, Australia, New Zealand, or the United Kingdom). If we also conduct this analysis for the lending sector, there are also countries in which most of the resources provided stem from the banking sector (for example, China, Australia, or Thailand), while others are provided through market based finance (MBF) (for example, Ireland, and Luxembourg). On the cross-country average, most of the borrowing debt is allocated to the non-financial firm sector, while most of the lending derives from the banking channel. Nevertheless, the averages from both the borrowing and lending sectors are relatively close. On the other hand, the values for the standard deviations are higher, pointing to a significant volatility, both within and across countries. This is especially the case for Argentina, Ireland and Luxembourg. The highest volatility is from the non-financial firm borrowing sector.

From the overall analysis, we can see that the average and standard deviation of the 2 lending channels are much closer than the 2 borrowing channels. We argue that we have a significantly diverse dataset, which accounts for heterogeneity across different countries, without focusing on specific borrowing or lending subsectors on average. We can also argue that there are some similarities across countries within the same regions/markets. For example, notice that the vast majority of European countries, or Euro Area countries, have a higher allocation of borrowed resources to the non-financial firm sector. On the other hand, some countries in the Anglosphere (UK, New Zealand and Australia) have a higher allocation of resources to the household sector. Finally, although we do not have a connection between the lending and borrowing subsectors, some countries that have a higher/lower bank lending share also have a higher/lower household borrowing share (this is the case of New Zealand, the UK, Luxembourg, Ireland, or Australia, for example). However, other countries in the sample defy this connection (Austria or Denmark, for example, shows a high share for non-financial firm debt, but also high share of bank lending. Or Norway, which shows a balanced borrowing sector, but also has a higher share of market based finance (MBF) channel). Thus, we do not go further on possible connections between the

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the information relevant for our dataset. Nevertheless, the majority of the sample is based on information from financial accounts.

2 lending and borrowing channels.

We move to Table 2.26, where we have an overall analysis of the different variables and statistics that are used[5]. The list of variables are as follows: y, $c^{Private}$, c^{H}, c^{NF}, c^{B}, c^{MBF}, d^{Gov}, $d^{NetForeign}$, c, c^{dur}, c^{nondur}, C/Y, i, g, x, m, NX/Y, CA/Y, s^{XC}, s^{MC}, $reer$, u, $y_{t+3|t}$, $\Delta_3 ln(P^{Housing})$, spr^{real}, spr^{MS}, spr^{corp}, EBP, and FCI denote log nominal GDP, private non-financial debt to GDP, household debt to GDP, non-financial firm debt to GDP, bank credit to GDP, market based finance (MBF) to GDP, government debt to GDP, change net foreign account (sum of current account to GDP surpluses), log nominal consumption, log nominal durable consumption, log nominal nondurable consumption, consumption to GDP, log nominal investment, log nominal government consumption, log nominal exports, log nominal imports, net exports to GDP, current account to GDP, the share of consumption exports to total exports, the share of consumption imports to total imports, log nominal effective exchange rate, the unemployment rate, the time t forecast of growth from t to t+3, the log real house price index, the real 10 year government bond yield spread with respect to the United States, mortgage-sovereign spread, the corporate-sovereign spread, the Excess Bond Premium, and Financial Conditions Index, respectively.

We start by the direct comparison between GDP (y) and total private non-financial sector debt to GDP ($c^{Private}$). We can see that, on average, GDP has been increasing by more than private debt (albeit being less volatile). When we subdivide by the 2 channels of the borrowing sector (recalling that total private non-financial sector debt is the sum of household debt and non-financial firm debt), as well as the 2 channels of the lending sector, we can also see the same conclusions we took from Table 2.25. Government debt level is also lower than GDP, but is also much more volatile. Net foreign account is lower, but the volatility is similar to the government debt. This volatility is much higher when we compare to the results displayed in [Mian et al., 2017a]. We believe this has to do with the inclusion of additional countries in our sample that have accumulated either public or external imbalances much more easily (Argentina, for example). For consumption, non-durables are less volatile than GDP, while durables seem to be more volatile than GDP, as well as investment. Imports and exports are roughly four times more volatile than output. Unemployment is relatively stable, while house prices are five times more volatile. All the spreads are significantly stable. All in all, most variables behaviour seems to be consistent with the literature on small open economy business cycle, as in [Mian et al., 2017a].

[5] All statistics are computed by compiling the observations from all available countries in our dataset.

2.4 Credit/Debt Variables and GDP Growth

2.4.1 Dynamic Relation

We resort to a regression framework to reflect the dynamic relation between GDP growth and changes in the 4 credit/debt variables (household debt, non-financial firm debt, bank credit and market based finance (MBF)). Consider y_{it} to be log GDP, α_i to be the country fixed effects, Δ_3 to be the changes over 3 years of the corresponding variable, c_{it}^H , c_{it}^{NF} be household and non-financial debt to GDP ratios, and c_{it}^B and c_{it}^{MBF} be bank credit and market based finance to GDP ratios, respectively. Mathematically, this can be expressed as:

$$\Delta_3 y_{it+k} = \alpha_i + \beta_H \Delta_3 c_{it-1}^H + \beta_{NF} \Delta_3 c_{it-1}^{NF} + \beta_B \Delta_3 c_{it-1}^B + \beta_{MBF} \Delta_3 c_{it-1}^{MBF} + u_{it+k} \tag{2.1}$$

for k = -1,0,...,5. As we can see, the time component of the right hand side of equation 2.1 is being kept constant, as the three year changes in the lagged value of the credit variables. That is, the change in credit from four years ago to last year, in the 4 different variables. On the left hand side, the three-year change in GDP growth is changing overtime, from the same period as the right hand side (last year), to five years into the future. For example, when k = 5, the different β on the right hand side would give the effect of an increase in the debt/credit in the corresponding channel from four years ago to last year, on the GDP growth from two years to five years into the future.

In Table 2.1, we see that the increase in bank credit over a three year period has initially a positive effect on GDP growth (in the contemporaneous period and lagged period), but then it turns negative in all subsequent periods. Not only that, almost all the coefficients are statistically significant. An increase in the market based finance (MBF) has an initial negative effect on GDP growth, which then turns into a positive effect (with the exception of the last period). However, none of them seem to be statistically significant. In most cases, the results in the equality tests point to the uniqueness of the pattern between both lending channels, as well as both borrowing channels. When we shift to the borrowing sector, we find mostly similarities and few discrepancies with the results presented in [Mian et al., 2017a]. In terms of similarities, we also find the boom and bust pattern of household credit, where an increase in household debt over a three-year period has a positive effect on GDP growth in the initial periods, but then turns negative in subsequent periods. We also find that the borrowing from non-financial firms has an initial negative impact on GDP growth, but then it turns positive. There is also statistical significance of the non-financial firm debt coefficients in both the short-term and long-term impacts, as well as the statistical significance of the household debt for the subsequent periods.

The main difference is in terms of the statistical significance of the household debt sector coefficients in the initial periods (when the effect is positive). In [Mian et al., 2017a], the au-

Table 2.1: Credit Expansion and Contemporaneous and Future Three-Year GDP Growth

	Dependent variable: $\Delta_3 y_{it+k}, k$ =-1,0,...,5						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta_3 y_{it-1}$	$\Delta_3 y_{it}$	$\Delta_3 y_{it+1}$	$\Delta_3 y_{it+2}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+4}$	$\Delta_3 y_{it+5}$
$\Delta_3 c^B_{it-1}$	0.2268*	0.004	-0.1387	-0.2198*	-0.2156**	-0.3288**	-0.4172**
	(0.0895)	(0.0904)	(0.0920)	(0.0929)	(0.0670)	(0.0913)	(0.08845)
$\Delta_3 c^{MBF}_{it-1}$	-0.1471	-0.1482	-0.0967	0.023	0.0473	0.0582	-0.0279
	(0.0963)	(0.0979)	(0.1011)	(0.1054)	(0.0762)	(0.0741)	(0.0704)
$\Delta_3 c^H_{it-1}$	0.6132**	0.6360**	0.4694**	0.2510$^+$	-0.2022*	-0.1768$^+$	-0.1837$^+$
	(0.1236)	(0.1247)	(0.1273)	(0.1290)	(0.0949)	(0.0959)	(0.0950)
$\Delta_3 c^{NF}_{it-1}$	-0.3697**	-0.3512**	-0.2269**	-0.0845	0.0181	0.0553	0.1199$^+$
	(0.0864)	(0.0869)	(0.0882)	(0.0887)	(0.0653)	(0.0654)	(0.0643)
Country fixed effects	✓	✓	✓	✓	✓	✓	✓
Test for equality (p-value):							
β_B and β_{MBF}	.0002	.1404	.6956	.0304	.0011	.0001	.0006
β_H and β_{NF}	.0000	.0000	.0000	.0453	.0802	.0705	.0179
R^2	0.1467	0.1310	0.0996	0.0800	0.0767	0.0845	0.0893
Observations	1,207	1,168	1,129	1,090	1,079	1,068	1,057

Notes: This table presents results from estimating the following specification $\Delta_3 y_{it+k} = \alpha_i + \beta_H \Delta_3 c^H_{it-1} + \beta_{NF} \Delta_3 c^{NF}_{it-1} + \beta_B \Delta_3 c^B_{it-1} + \beta_{MBF} \Delta_3 c^{MBF}_{it-1} + u_{it+k}$ for k = -1, ..., 5. Each column gradually leads the left-hand-side variable by one year. Reported R^2 values are from within-country variation. Standard errors in parentheses are dually clustered on country and year. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

thors find that the positive effect estimations are not statistically significant, while the negative effect estimations are statistically significant. As we can see in Table 2.1, we find that both are significant, especially the positive effects. In order to understand why, we further estimate our results for specific subsamples. The first scenario is to remove the lending sector variables from the estimation equation. In this case, the results we obtain are similar to the ones in [Mian et al., 2017a] (that is, the positive coefficients for household debt in the initial periods are no longer statistically significant). This is also the case when we restrict our sample for the same period considered in the aforementioned article, where we also obtain similar results. Therefore, this offers 2 possibilities that explain the difference in the results. The first one is that the other coefficients capture the effects of the household debt coefficient, rendering it less statistically significant. However, this is unlikely to be the case, as the household debt has become more significant in the initial periods as well, not less. Thus, it is not a decrease in the statistical significance of the coefficient, but instead, an increase of the significance towards the positive short-term periods. This would point to, instead, considering more recent periods in the sample, which seem to encompass more positive effects in the short-term for household debt. Finally, when we just estimated the model for the 2 lending channels, we find that there is a higher statistical significance for the market based finance (MBF) coefficient. The negative impact estimations for the initial periods were statistically significant, while the positive impact estimations for the subsequent periods were not statistically significant.

2.4.2 Single equation estimation

To further explore the results in the previous subsection, we focus on the $\Delta_3 y_{it+3}$ case, that is, on the impact of an increase in the credit/debt variables from four years ago to the previous year, as in [Mian et al., 2017a]. We now consider the following estimation:

$$\Delta_3 y_{it+3} = \alpha_i + \beta_H \Delta_3 c^{H}_{it-1} + \beta_{NF} \Delta_3 c^{NF}_{it-1} + \beta_B \Delta_3 c^{B}_{it-1} + \beta_{MBF} \Delta_3 c^{MBF}_{it-1} + X'_{it-1}\Gamma + \varepsilon_{it+k} \quad (2.2)$$

This would be a similar estimation to equation 2.1, with 2 differences: 1 - we focus on the k = 3 case for the left-hand side of the equation; 2 - we add additional control variables, as represented by the X_{it-1}, which includes lags of the dependent variable, to make sure that the results are not justified by mean-reversion of GDP growth. In most scenarios, we only include country fixed effects, but we will also include period fixed effects in additional scenarios. We dually cluster standard errors on country and period to incorporate any within country correlation and contemporaneous cross-country correlation in the error term. In particular, this accounts for within country correlation induced by overlapping observations.

The results are displayed on Table 2.2, from estimating GDP growth from t to t + 3 on the change in total private non-financial sector, household, and non-financial firm debt to GDP, as well as bank credit and market based finance (MBF) to GDP, from the end of t - 4 to the end of t - 1. Columns 5-8 control for three lags of GDP growth over the same period as the change in debt to GDP, $\Delta_3 y_{it-1}$, $\Delta_3 y_{it-2}$, and $\Delta_3 y_{it-3}$. Column 6 includes the increase in government debt to GDP over the same period, and column 7 controls for the change in net foreign account, calculated as the sum of current account surpluses to GDP over the same 3-year period. Column 8 combines both variables that we add in columns 6 and 7. Column 9 interacts the increase in all 4 types of credit with a dummy for whether the cumulated current account over the same period is negative. All specifications include country fixed effects.

We start with column 1, where we have the effect of total non-financial private sector debt on GDP growth. The coefficient is negative, and is statistically significant. In the next 3 columns (columns 2 to 4), we separate total non-financial private sector debt between the 2 components of the borrowing sector (household debt + non-financial firm debt) and the lending sector (banking channel market based finance (MBF) channel). As we can see, the negative impact is driven by the household debt, on the borrowing sector side, and the bank credit, on the lending sector side. Both of them are statistically significant throughout the different scenarios. However, the total impact is hampered due to the positive effect of market based finance (MBF) lending channel, for which we find some statistical significance when the coefficient is positive, and, on a smaller scale, from the non-financial firm debt, in the last scenario. In the majority of these scenarios, both tests for the difference between the 2 borrowing channels and the 2 lending channels are statistically significant.

In addition, we present a scatter plot in Figure 2.2 in the appendix, which presents the relationship between GDP growth and each of the 4 credit variables. For household debt and bank credit, the relationship is clearly negative, and not a result from the outliers in our sample, reflecting the same conclusions we took from Table 2.2 so far. For the case of non-financial firm debt, the relationship also seems negative, but it is much less pronounced than the previous 2 cases. For the market based finance (MBF), it seems to show a lack of relationship between the 2 variables.In column 5 of Table 2.2, we include the lagged one-year GDP growth variables, Δy_{it-1}, Δy_{it-2} and Δy_{it-3}. The estimations of the coefficients for the household debt and the bank credit remain statistically significant, implying that the results are not driven by the possibility of spurious mean reversion in the GDP growth. In column 6, we include the 3-year change in public debt to GDP ratio (over the same period as the remaining right-hand side variables). An increase in public debt to GDP results in a significant fall of economic growth over the next three years, which is statistically significant.

In columns 7-9, we study the potential impact of the accumulation of net foreign surpluses, and its possible correlation with the 4 credit/debt variables in the model. The main reason why we add this variable is due to theoretical models disagreeing on whether the main relevance of the impact of debt on GDP is related to debt within country, or the accumulation of debt vis-á-vis the rest of the world. In column 7, we can see that a higher surplus has a positive impact on GDP growth (therefore, the reverse, being the accumulation of net foreign debt, is likely to have a negative influence), and it is statistically significant. Not only that, in column 8, when we use both government debt and net foreign surplus, we can see both variables remain statistically significant (although the coefficients decrease a bit in their magnitude). Also notice that, even with the inclusion of these 2 additional variables, the household debt and bank credit coefficients still remain statistically significant.

Table 2.2: Credit Expansion with additional controls

	Dependent variable: $\Delta_3 y_{it+3}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta_3 c^{Private}_{it-1}$	-0.072*								
	(0.0361)								
$\Delta_3 c^{B}_{it-1}$		-0.2215**		-0.2156**	-0.2362**	-0.1866**	-0.1210^{+}	-0.1772*	-0.1154**
		(0.0619)		(0.0670)	(0.0690)	(0.0962)	(0.0706)	(0.0709)	(0.0323)
$\Delta_3 c^{MBF}_{it-1}$			0.1407*	0.0473	-0.0108	0.1960^{+}	-0.1024	-0.0452	-0.0271
			(0.0708)	(0.0762)	(0.0777)	(0.1082)	(0.0800)	(0.0804)	(0.0350)
$\Delta_3 c^{H}_{it-1}$		-0.2034*	-0.3392**	-0.2022*	-0.2057*	0.0343	-0.2644**	-0.2261*	-0.0747^{+}
		(0.0948)	(0.0852)	(0.0949)	(0.0951)	(0.1329)	(0.0936)	(0.0931)	(0.0410)
$\Delta_3 c^{NF}_{it-1}$		0.0472	-0.0758	0.0181	0.0060	0.0027	0.0505	0.0357	0.0718*
		(0.0454)	(0.0587)	(0.0653)	(0.0904)	(0.0882)	(0.0642)	(0.0642)	(0.0315)
$\Delta_3 d^{Gov}_{it-1}$						-0.3028**		-0.2406**	
						(0.0904)		(0.0505)	
$\Delta_3 d^{Net foreign}_{it-1}$							0.3136**	0.2676**	
							(0.0614)	(0.0619)	
$\mathbf{1}(\Delta_3 d^{Net foreign}_{it-1} < 0)$									-0.0244
									(0.5313)
$\Delta_3 c^{B}_{it-1} * \mathbf{1}(\Delta_3 d^{Net foreign}_{it-1} < 0)$									-0.0942^{+}
									(0.0494)
$\Delta_3 c^{MBF}_{it-1} * \mathbf{1}(\Delta_3 d^{Net foreign}_{it-1} < 0)$									0.1041^{+}
									(0.0541)
$\Delta_3 c^{H}_{it-1} * \mathbf{1}(\Delta_3 d^{Net foreign}_{it-1} < 0)$									-0.0954
									(0.0695)
$\Delta_3 c^{NF}_{it-1} * \mathbf{1}(\Delta_3 d^{Net foreign}_{it-1} < 0)$									-0.0630
									(0.0448)
Country fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Distributed lag in Δy					✓	✓	✓	✓	✓
Test for equality (p-value):									
β_B and β_{MBF}				.0011	.0050	.0010	.8231	.1503	.0241
β_H and β_{NF}		.0308	.0364	.0802	.0911	.8539	.0108	.0340	.0120
R^2	0.0428	0.0765	0.0700	0.0767	0.1093	0.1321	0.1147	0.1360	0.1385
Observations	1,697	1,079	1,079	1,079	1,079	1,012	967	950	950

Notes: This table presents results from estimating GDP growth from t to t + 3 on the change in total private non-financial sector, household, and non-financial firm debt to GDP, as well as bank credit and market based finance (MBF) to GDP, from the end of t - 4 to the end of t - 1. Reported R^2 values are from within-country variation. Standard errors in parentheses are dually clustered on country and year. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively. More detail is provided in subsection 2.4.2

In the final column, we interact the expansion in each 4 types of credit/debt with a dummy for whether the cumulated current account over the same period is negative. Interestingly enough, the results seem to show that the interaction coefficients for bank credit and both borrowing channels are negative, while they are positive for the market based finance (MBF). Nevertheless, only the lending channel's coefficients are statistically significant. Thus, we can say that a higher current account deficit amplifies the effects of both lending channels on GDP growth, which are negative for the bank credit and positive for the market based finance (MBF). The accumulation of current account deficits are likely to leave countries even more exposed to the internal effects of credit (whether they are positive or negative), as the economy is likely to have fewer resources to counteract these effects. Finally, when we restricted the analysis to exclude the borrowing sector variables, again, we find more significance for the market based finance (MBF) lending for some of the scenarios described here. However, the bank lending channel still remains statistically significant for all scenarios.

Lastly, in Figure 2.3, we have the estimated coefficients from equation 2.2, for each of the 4 types of credit/debt, for each country. If we start our analysis with the bank credit coefficients, we can see that the number of positive and negative coefficients is more or less even, with a small difference in favour of the negative coefficients. However, in terms of the magnitude, there are more large negative coefficients than large positive coefficients, which would explain the negative impact overall on GDP. The lowest one would be Brazil, around -2.80, but also accompanied by Canada, Chile, Czech Republic and Turkey. The more significant positive contribution is from India, with an increase in bank credit having a positive impact on GDP higher than 2 units. When we shift to market based finance (MBF), not only do we have more countries with positive than negative coefficients, but also the positive coefficients seem larger in terms of magnitude. Countries with significant positive MBF include Germany (with the highest at 2.38), Greece, India, and Poland, while the opposite effect reflects in Austria, Malaysia, Mexico, the Netherlands, and South Africa. For household debt, we have an almost even scenario of positive and negative cases. We also have extreme cases, in our sample, where some countries show significant positive and negative coefficients. This seems to be in contrast with the results in [Mian et al., 2017a], in which only 6 out of the 30 countries have a positive coefficient, and there are not many extreme estimations. However, we argue that: 1 - the extreme scenarios are from countries not taken into account in their sample (the large negative coefficients are from Argentina (-13.16) and Brazil (-7.62), and the positive ones are from China (5.45), and South Africa (10.768)); 2 - the average value of the coefficient for the household debt is close to the original value, which would imply that, even though we have more countries in our sample with positive household debt coefficients, when compared with their case, the countries with negative coefficients have a higher impact. For non-financial firm debt, we have more cases of positive coefficients than negative coefficients. The more significant negative coefficients would be Brazil and Turkey, while the highest positive coefficient is South Africa.

2.4.3 Robustness and Subsamples

We include robustness checks on possible bias for sample selection, standard errors, estimation methods, and functional form for the credit/debt variables. We begin with Table 2.3, which provides the estimation results with different specifications. In the first column, we only use non-overlapping years for the GDP growth, to make sure our results do not stem from repeated observations. That is, we only include each third year (Δ between year t=0 and t =3, then between year t=4 and t=7, and so on). The estimated values, standard errors and statistical significance seem to maintain the same conclusions we took previously (the only possible change is a decrease of the magnitude of the household debt coefficient). On a possible issue that we may have inadvertently in our estimations of equation (2) is the "Nickell bias", due to the inclusion of country fixed effects and lagged dependent variables. Even given the likelihood of a small bias (due to the long range of the panel data), we resort to the [Arellano and Bond, 1991] GMM estimator for the same scenario of column 1, instead of the OLS estimator. We instrument for $\Delta_3 c^n_{it-1}$, with a double lag, $\Delta_3 c^n_{it-4}$, where n = {B, H, NF, MBF}, as well as the lags of three years of GDP growth. Although the magnitude and statistical significance of the bank credit remains, we can see there is a significant decrease of the magnitude of the household debt coefficient, and it loses the statistical significance. Therefore, we could have a "Nickell bias" issue for the house credit. Nevertheless, this does not seem to be the case when we check the information provided in column 3. In here, we abdicate the country fixed effects, and we see that both the bank credit and household debt maintain their statistical significance.

We move to changes in the robustness of standard errors. Until now, we considered standard errors that are robust to correlation in the errors within countries over time and across countries in a given year. In column 4, we relax this constraint, allowing for residual correlation across different countries in a specific period, and within countries over different periods. For this, we resort to the panel moving blocks bootstrap method, applied by [Gonçalves, 2011], which re-samples the data using the moving block bootstrap on the vector containing all countries in a given period[6]. As we can see, especially for the bank credit, this leads to a relative drop in the magnitude of the coefficient, and an increase of the standard error, but still clearly maintains it's statistical significance. For the house credit, there is but a small rise in the standard error.

In columns 5 and 6, we include a time trend and period fixed effects, respectively. When we include either of these 2 options, it leads to a decline of the bank credit coefficient, while the household debt coefficient seems to maintain its value. Either way, both coefficients retain their statistical significance, at 1%. Not only that, it also seems that the market based finance (MBF) becomes statistically significant in both scenarios, at a 5% level, with a positive effect on GDP growth in three years.

In the last column, we apply a different definition for the increase in debt/credit, by simply

[6]We present the standard errors for the block length that produces the highest standard errors, which, in our case, leads to a block length of l = 3 years.

Table 2.3: Credit Expansion Predicts Future GDP Growth: Robustness to Alternative Specifications

	Dependent variable: $\Delta_3 y_{it+3}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	AB-GMM	OLS	MBB SE	OLS	OLS	OLS
$\Delta_3 c^{B}_{it-1}$	-0.2755**	-0.2310*	-0.1798**	-0.1259**	-0.1441**	-0.1172**	
	(0.0873)	(0.1174)	(0.0252)	(0.0321)	(0.0223)	(0.0203)	
$\Delta_3 c^{MBF}_{it-1}$	-0.0462	0.0132	0.0343	0.0370	0.0496*	0.0496*	
	(0.1117)	(0.0337)	(0.0263)	(0.0313)	(0.0248)	(0.0224)	
$\Delta_3 c^{H}_{it-1}$	-0.1119**	-0.0024	-0.1040**	-0.1045**	-0.1164**	-0.1093**	
	(0.0377)	(0.1428)	(0.0334)	(0.0376)	(0.0300)	(0.0277)	
$\Delta_3 c^{NF}_{it-1}$	0.1008	0.1429	0.0247	0.0356	0.0059	-0.0080	
	(0.1061)	(0.1369)	(0.0234)	(0.0269)	(0.0204)	(0.0188)	
Trend					-0.2564**		
					(0.0188)		
$\Delta_3 c^{B}_{it-1}$, alt. norm.							-0.0619**
							(0.0202)
$\Delta_3 c^{MBF}_{it-1}$, alt. norm.							0.0385^{+}
							(0.0217)
$\Delta_3 c^{H}_{it-1}$, alt. norm.							-0.0542*
							(0.0270)
$\Delta_3 c^{NF}_{it-1}$, alt. norm.							-0.0170
							(0.0200)
Country fixed effects	✓			✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓	✓
Year fixed effects						✓	
Sample	Non-overl.	Non-overl.	Full	Full	Full	Full	Full
Test for equality (p-value):							
β_B and β_{MBF}	.0242	.0030	.0000	.0000	.0000	.0000	.0000
β_H and β_{NF}	.0130	.4777	.0031	.0030	.0017	.0055	.0200
R^2	0.3166		0.3515	0.3440	0.2713	0.6116	0.4312
Observations	529	514	1,079	1,079	1,079	1,079	1,079

Notes: This table shows several tests for robustness of the main scenario described in Table 2.2. In Column 1, we have the non-overlapping sample. That is, we only include each third year (Δ between year t=0 and t =3, then between year t=4 and t=7, and so on). This specification controls for $\Delta_3 y_{it-1}$. In Column 2, instead of the OLS estimation, we resort to the Arellano-Bond GMM estimator for the equation in differences on the same non-overlapping sample. We instrument for $\Delta_3 c^{n}_{it-1}$, with a double lag, $\Delta_3 c^{n}_{it-4}$, where n = {B, H, NF, MBF}, as well as the lags of three years of GDP growth. In Column 3, we shift towards the full sample, and do not consider country fixed effects. Column 4 computes standard errors using the panel moving blocks bootstrap ([Gonçalves, 2011]) with a block length of l = 3. Column 5 includes a time trend, and column 6 includes year fixed effects. Column 7 replaces the three-year change in debt/credit to GDP with the change in debt/credit normalized by initial (t-4) GDP. Standard errors in all columns (except column 4) are dually clustered on country and year. Reported R^2 values in regressions including country fixed effects are from within-country variation. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table 2.4: Credit Expansion Predicts Future GDP Growth: Subsamples

	Dependent variable: $\Delta_3 y_{it+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 c^B_{it-1}$	-0.2120**	-0.6137$^+$	-0.4535**	-0.1618*	-0.1090**	-0.0949**
	(0.0623)	(0.3450)	(0.1436)	(0.0716)	(0.0296)	(0.0214)
$\Delta_3 c^{MBF}_{it-1}$	0.0475	0.2006	-0.0700	-0.0126	0.0561$^+$	0.0486*
	(0.0686)	(0.4129)	(0.1376)	(0.0788)	(0.0321)	(0.0229)
$\Delta_3 c^H_{it-1}$	-0.1356$^+$	-0.2606	-0.1824**	-0.1712$^+$	-0.1018*	-0.1025**
	(0.0795)	(0.8333)	(0.0673)	(0.0962)	(0.0402)	(0.0282)
$\Delta_3 c^{NF}_{it-1}$	0.0307	-0.1372	0.0424	-0.0002	-0.0022	-0.0080
	(0.0589)	(0.3109)	(0.0340)	(0.0649)	(0.0246)	(0.0188)
Trend					-0.2210**	
					(0.0288)	
Country fixed effects	✓	✓	✓	✓	✓	✓
Distributed lag in Δy	✓	✓	✓	✓	✓	✓
Year fixed effects						✓
Sample	Developed	Emerging	Pre 1995	Pre 2006	Pre 2006	Pre 2006
Test for equality (p-value):						
β_B and β_{MBF}	.0002	.1234	.0282	.0820	.0000	.0000
β_H and β_{NF}	.1200	.9047	.0114	.1802	.0735	.0116
R^2	0.1255	0.1496	0.3762	0.2356	0.3143	0.6789
Observations	803	232	288	569	569	569

Notes: This table reports estimates on various subsamples. Columns 1 and 2 present separate estimates for developed and emerging economies. For this classification, we use the IMF and World Bank Data available at: https://www.worlddata.info/developing-countries.php. In our sample, we have a total of 100 emerging economies, while the remaining 36 countries are considered developed countries. Column 3 uses data up to 1995, and columns 4-6 use data up to 2006. Column 5 includes a time trend, and column 6 controls for year fixed effects. Standard errors in all columns are dually clustered on country and year. Reported R^2 values in regressions including country fixed effects are from within-country variation. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

scaling the change in the debt/credit variables with GDP from four years ago (i.e., $\Delta_3 c^m_{it-1} = \frac{D^m_{it-1} - D^m_{it-4}}{Y_{it-4}}$, where m = { H, NF}, and $\Delta_3 c^n_{it-1} = \frac{C^n_{it-1} - C^n_{it-4}}{Y_{it-4}}$, where n = { B, MBF}). In our estimations, this leads to a decrease of the magnitude of all coefficients, with the exception of the non-financial firm debt, which is not statistically significant. All other coefficients are statistically significant, with the bank credit maintaining its significance at 1%. In all specifications, the difference between the estimated coefficients on the increase in bank credit and market based finance is statistically significant at 5%, with all but one significant at 1%. For the difference between household debt and non-financial firm debt, all but one are significant at 5%.

For the analysis within subsamples, we turn to Table 2.4. Columns 1 and 2 show the analysis when we divide between developed countries and emerging economies. For developed countries, our results maintain, both in terms of the value of the estimated coefficients, but also in terms of significance, for the household debt and the bank credit alike (even though there seems to be lower significance for the household debt, only being significant at 10%). When we shift the analysis towards the emerging economies, there is a decrease of statistical significance for the bank credit, and its magnitude almost triples. For the household debt coefficient, the values almost double, and ceases to be significant. This result does not match the one reported by [Mian et al., 2017a], who find that the magnitude of the household debt coefficient decreases for emerging economies, but still retains its statistical significance. The difference in the results may be explained by the difference in the number of emerging economies considered in the sample. In their case, they consider a total of 10 emerging economies, while, in our case, we consider 100. It could also be that the definition that we use for emerging economies is not the same that they consider, leading to a different list of countries in each subsample. Finally, it could be that the coefficient loses significance in the subsample, when we add the lending sector variables. When we re-estimate column 2 just for the borrowing sector variables, the household debt coefficient still does not become statistically significant. From a closer analysis, we can see that the main difference is the increase in the standard errors, in all the variables, for the emerging economies subsample. This is not the case for the [Mian et al., 2017a] scenario, where the standard errors decrease slightly. Thus, we can conclude that the difference stems from the higher number of countries considered in the emerging economies subsample, and the large volatility within the subsample.

In the next 2 columns, we provide time constraints. More specifically, column 3 just considers the years until 1995, and column 4 until 2006. The main goal is to be certain that the negative impact on future economic growth (and statistical significance) of both the household debt and bank credit are not just connected to the boom and bust cycle around the Great Financial Crisis. This is the case in our sample, as both coefficients retain their statistical significance in both cases. We can also see that the bank credit coefficient has a larger magnitude in the periods before 1995, pointing to a higher relevance of the bank sector in those periods. In the last 2 columns we, again, consider a time trend and period fixed effects, but just for the subsample until 2006. Although there is a fall in the magnitude in both coefficients, they retain their statistical significance. Not only that, the market based finance coefficient also becomes significant, with a positive, but moderate, impact on GDP growth.

In terms of the difference between coefficients in the lending sector, almost all scenarios retain the significance of this difference, with the exception of the emerging economies subsample. For the difference between coefficients in the borrowing sector, only half of the scenarios retain the significance. When we exclude the borrowing sector variables from the estimation, there is an increase in the significance of the market based finance, both in the subsample and the alternative specification analysis. Nevertheless, the bank credit remains the variable with higher statistical significance, and for more scenarios. For example, in the subsample analysis, the market based finance becomes statistically significant for the developed economies, but not for the emerging economies.

2.4.4 Initial impact on the rest of the economy

So far, we have focused our analysis on the correlation between the three-year change in the 4 debt/credit variables, and subsequent output growth. Now, we turn to the analysis of the contemporaneous impact of debt/credit changes on the different variables of the real economy. This is reflected in Table 2.5, where we consider the same period correlation between the changes in the debt/credit to GDP ratios, with consumption, investment, and trade. We begin with overall consumption, described in column 1. Both household debt and bank credit show a positive and statistically significant coefficient, although it is small in magnitude. The non-financial firm debt shows a negative impact, also statistically significant. When we decompose consumption between durables, non-durables, and services, we can see that bank credit has a positive influence on the consumption of services and non-durables. And even though the impact on durables is negative, it is not statistically significant. This could be interpreted as a lack of a connection between the household debt and bank credit. Given that the main destination of household debt is mortgage credit, which would fall under the category of durable goods, and one would expect most households resorting to bank credit instead of market based finance, one would expect the coefficient for consumption of durables associated with bank credit to be positive, which is not the case. This would point to bank lending and household debt being statistically significant on an individual basis, and not because most bank lending is contracted by the household sector. However, given that we do not have the specific allocations between the each of the 2 subsectors of lending and borrowing, we do not develop on this assertion.

This conclusion is reinforced when we shift the analysis towards household debt, there is a negative impact on the consumption of non-durables and services, and positive impact on durables, which is the opposite of the bank credit. This would be expected, given that the main destination of household credit would be mortgage credit, which falls under the category of durable goods. The non-financial firm debt also shows coefficients which are statistically significant, with opposite direction in each case from the household debt. In terms of investment, all coefficients show a negative impact, but only the market based finance (MBF) is statistically significant. Nevertheless, the magnitude is very small, pointing to an almost flat impact on investment during the boom debt/credit period.

In terms of the impact on the trade sector, both bank lending and household debt are negatively correlated with net exports and current account to GDP ratio (columns 6 and 7). For non-financial firm debt, it seems to be positively associated with net exports. Given the increase in imports over exports during an increase of bank credit or household debt, we further attempted to identify in which sector this change would occur. When we included the potential impact on the share of consumption imports and exports (columns 8 and 9, respectively), we do not find statistical significance in any of the coefficients.

Table 2.5: Impact on different variables during Boom phase

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\Delta_1 \frac{C}{Y}_{it}$	$\Delta_1 \frac{C^{nondur}}{Y}_{it}$	$\Delta_1 \frac{C^{dur}}{Y}_{it}$	$\Delta_1 \frac{C^{services}}{Y}_{it}$	$\Delta_1 \frac{I}{Y}_{it}$	$\Delta_1 \frac{NX}{Y}_{it}$	$\Delta_1 \frac{CA}{Y}_{it}$	$\Delta_1 s_{it}^{MC}$	$\Delta_1 s_{it}^{XC}$
$\Delta_1 c_{it}^{B}$	0.0402**	0.3308**	-0.0140	0.5094**	-0.0080	-0.0441**	-0.0594**	0.0339	0.0103
	(0.0094)	(0.0708)	(0.0141)	(0.1178)	(0.0146)	(0.0145)	(0.0174)	(0.0342)	(0.0575)
$\Delta_1 c_{it}^{MBF}$	0.0074	-0.0098	0.0126	-0.0503	-0.0273^{+}	-0.0124	-0.0031	0.0272	0.0367
	(0.0091)	(0.0573)	(0.0131)	(0.0954)	(0.0141)	(0.0141)	(0.0167)	(0.0334)	(0.0562)
$\Delta_1 c_{it}^{H}$	0.0454**	-0.4066**	0.0337^{+}	-0.6099**	-0.0074	-0.0461*	-0.0374^{+}	-0.0013	-0.0124
	(0.0123)	(0.0988)	(0.0204)	(0.1643)	(0.0190)	(0.0188)	(0.0227)	(0.0449)	(0.0755)
$\Delta_1 c_{it}^{NF}$	-0.0181*	0.1091*	-0.0208^{+}	0.1764*	-0.0085	0.0207^{+}	0.0142	0.0013	-0.0004
	(0.0073)	(0.0516)	(0.0123)	(0.0858)	(0.0113)	(0.0115)	(0.0135)	(0.0276)	(0.0463)
Country fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.0665	0.0637	0.1551	0.0716	0.0290	0.0437	0.0230	0.0033	0.0020
Observations	1,273	577	698	577	1,273	1,139	1,217	1,202	1,195

Notes: This table presents the correlation between the current change in each of the 4 debt/credit variables, and the current change in several economic variables, including: the change in the total consumption to GDP ratio, non-durable consumption to GDP, durable consumption to GDP, services consumption to GDP, investment to GDP, net exports to GDP, current account to GDP, the share of consumption imports in total imports, and the share of consumption exports in total exports. All specifications include country fixed effects. Reported R^2 values are from within-country variation. Standard errors in parentheses are dually clustered on country and year. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

2.5 IV - Instrumental Variable Regressions

Some of the results we obtained from the previous section would point against the possibility of a credit demand shock being the fundamental cause of the effects on the credit/debt variables. For example, in traditional models, with rational expectations, a credit demand shock is unlikely to lead to a decrease in subsequent economic growth, due to an increase in the household debt. The same reasoning is applied in the case of higher bank lending. If this simply results from the demand side of credit, it implies that there is no relaxation of lending conditions (no lowering of borrowing costs, like interest rates charged, or additional regulations or constraints). This would imply either that borrowers would have better conditions to increase their borrowing amount, or that they would be willing to sustain higher borrowing costs. In either case, one would not expect bank lending increase to lead to a lower GDP growth in subsequent periods. That relation is more likely in the case of a credit supply shock, where credit lending standards or costs would be lowered. This is more fitting to our results, where the initial impact on GDP growth is positive, due to higher spending connected to higher borrowing. However, as lower lending standards/costs provide credit to lower quality borrowers, or higher amounts of credit to regular borrowers, the bursting of the credit bubble would lead to defaults and non-repayment by the borrowers, justifying lower GDP growth in the subsequent periods.

Nevertheless, we need to explore the possibility of either scenario. In this section, we resort to an IV (Instrumental Variable) regression, considering a list of different instruments, and see whether the results point to a credit demand shock, or credit supply shock. We begin by using the same instruments as in [Mian et al., 2017a], which consists of three spreads: the real sovereign spread (spr^{real}), the mortgage sovereign spread (spr^{MS}), and the corporate credit spreads (spr^{corp}). We, then, add three additional instruments to our analysis: the Excess Bond Premium (EBP), the Financial Conditions Index (FCI), and the Principal Component (PCA), which is a combination of all the previous instruments, using the first and second principal components to construct the final instrument, and the amount of total variation explained of each component as the weights (the first explains around 56% of all the variation, while the second explains around 29% of all the variation, with a total of 85%).

2.5.1 Interest Spreads: Real Sovereign Spread

We begin with the impact of interest rates on the 4 different credit/debt variables. The main reason is that models that evaluate the impact of interest rates on the debt of households or bank credit offer opposing predictions between credit demand and credit supply shocks.

First, we examine the scenario with the real sovereign spread (spr^{real}). This is connected to the significant changes in Eurozone countries before the Great Financial Crisis, and the impact on sovereign spreads, credit change variables, and GDP growth. More specifically, we follow [Mian et al., 2017a], and establish that a lowering of the sovereign spreads in relation to the United States Treasuries can be used as a potential proxy of a credit supply shock for the Eurozone countries in the years before the Great Financial Crisis. This assertion is connected to the introduction of the single currency (the euro), which translated to a convergence of sovereign spreads between the core and peripheral Eurozone countries, due to a lower currency and other risk premia. As expected, the lower spreads led to a higher credit supply in the peripheral countries, since they had higher spreads when compared to core countries, and benefited on a disproportional basis from the converging process of the sovereign spreads. This convergence in the Eurozone sovereign spreads over the 10 year United States Treasuries can, thus, be used as an instrument for the expansion in each of the 4 credit/debt variables in the Eurozone countries, resorting to a two stage least squares (2SLS) estimation procedure:

$$\Delta_{02-07} c_i^n = \alpha^f + \beta^f * z_i + u_i^f \tag{2.3}$$

$$\Delta_{07-10} y_i = \alpha^s + \beta^s * \Delta \hat{c}_i^n + u_i^s \tag{2.4}$$

Where n = { B, MBF, H, and NF}. The application of the remaining instruments will follow a similar structure, the main difference will be the sub-periods taken into account in the estimation. The results are shown in Tables 2.6 and 2.7.

Table 2.6: Instrumental Variable: Sovereign Spread Convergence in the Eurozone - Borrowing sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_{07-10}y_i$	$\Delta_{07-10}y_i$	$\Delta_{02-07}c_i^H$	$\Delta_{07-10}y_i$	$\Delta_{02-07}c_i^{NF}$	$\Delta_{07-10}y_i$	$\Delta_{07-10}y_i$	$\Delta_{07-10}y_i$
$\Delta_{96-99}spr_i^{real}$			-0.0387*		-0.9138**			
			(0.0191)		(0.2089)			
$\Delta_{02-07}c_i^H$	-0.1897**			-0.3693**			-0.6127**	-0.1124*
	(0.0180)			(0.0183)			(0.1438)	(0.0529)
$\Delta_{02-07}c_i^{NF}$		0.1364**				0.9007**	0.0394^{+}	0.3206**
		(0.0170)				(0.2012)	(0.0220)	(0.0869)
$\Delta_{02-07}y_i$							0.6461**	-0.3118^{+}
							(0.2165)	(0.1685)
Equation	OLS	OLS	FS	IV	FS	IV	IV	IV
First stage F-statistic			4.11		7.74			
R^2	0.1296	0.1870	0.1115	0.1103	0.1470	0.1423	0.3362	0.3599
Observations	12	12	12	12	12	12	12	12

Notes: This table reports instrumental variables regressions of GDP growth from 2007 to 2010 on the expansion in debt of the 2 segments of the borrowing sector: household debt to GDP from 2002 to 2007, and expansion of non-financial firm debt to GDP from 2002 and 2007. Columns 1 and 2 show the OLS estimate for the Eurozone countries. Columns 3-6 use the change in the real sovereign spread (nominal spread minus inflation difference) with respect to the United States during 1996-1999 as an instrument for the 2002-2007 expansion in household or firm debt to GDP. Column 7 adds described variables when we use household debt as the dependent variable in the First Stage, while column 8 adds described variables when we use non-financial firm debt as the dependent variable in the First Stage. Standard errors in parentheses are robust to heteroskedasticity. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table 2.7: Instrumental Variable: Sovereign Spread Convergence in the Eurozone - Lending sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_{07-10}y_i$	$\Delta_{07-10}y_i$	$\Delta_{02-07}c_i^B$	$\Delta_{07-10}y_i$	$\Delta_{02-07}c_i^{MBF}$	$\Delta_{07-10}y_i$	$\Delta_{07-10}y_i$	$\Delta_{07-10}y_i$
$\Delta_{96-99}spr_i^{real}$			-0.2550**		-1.5645**			
			(0.0831)		(0.0978)			
$\Delta_{02-07}c_i^B$	-0.0860**			-0.2284**			-0.4046**	-0.0136
	(0.0151)			(0.1643)			(0.1057)	(0.0234)
$\Delta_{02-07}c_i^{MBF}$		0.4307**				0.5261**	0.0088	0.6504**
		(0.0170)				(0.0318)	(0.0450)	(0.1782)
$\Delta_{02-07}y_i$							0.7139**	0.0496
							(0.1853)	(0.1078)
Equation	OLS	OLS	FS	IV	FS	IV	IV	IV
First stage F-statistic			12.24		8.15			
R^2	0.0467	0.4470	0.1663	0.1652	0.0821	0.0809	0.4626	0.0996
Observations	12	12	12	12	12	12	12	12

Notes: This table reports instrumental variables regressions of GDP growth from 2007 to 2010 on the expansion in credit of the 2 segments of the lending sector: bank credit to GDP from 2002 to 2007, and market based finance to GDP from 2002 and 2007. Columns 1 and 2 show the OLS estimate for the Eurozone countries. Columns 3-6 use the change in the real sovereign spread (nominal spread minus inflation difference) with respect to the United States during 1996-1999 as an instrument for the 2002-2007 expansion in bank credit or market based finance to GDP. Column 7 adds described variables when we use bank credit as the dependent variable in the First Stage, while column 8 adds described variables when we use market based finance as the dependent variable in the First Stage. Standard errors in parentheses are robust to heteroskedasticity. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

If we start with columns 1 and 2, or Figure 2.4 in the Appendix, when we restrict our sample to the Eurozone countries, and the variables in question to the before mentioned periods, each of the 4 debt/credit variables have a statistically significant impact on GDP growth. While household debt and bank credit have a negative influence, non-financial firm debt and market based finance have a positive impact. In columns 3 to 6, or Figure 2.5 in the Appendix, confirms the likelihood of resorting to the decrease of the real sovereign spread from 1996 to 1999, between a Eurozone country's 10 year government bond and the United States 10-year Treasury yield, as the potential credit supply shock z_i in equation 2.4. All 4 credit/debt variables show a negative and statistically significant coefficient in the First Stage (columns 3 and 5), implying that a fall in the real sovereign spread led to a rise in credit/debt during these periods. Thus, Eurozone countries which had a larger decline in their real sovereign yield spread from 1996 to 1999 also witnessed a more robust expansion in credit/debt to GDP between 2002 and 2007. The Second Stage impact (columns 4 and 6) follow the same reasoning we provided in columns 1 and 2. In columns 7 and 8, we add the contemporaneous change of GDP between 2002 and 2007, as well as the other credit/debt variable of the corresponding sector. All the coefficients retain their significance. The only exceptions is the market based finance (when we use the bank credit as the dependent variable in the First Stage), and vice-versa.

When it comes to household debt, the results we have are similar to those obtained by [Mian et al., 2017a], with one exception: the First Stage coefficient for the impact of the real sovereign spread on the change in household debt is much larger than the one we find here. This is highly likely connected to the different source of the data for the real sovereign spread, spr^{real}, as we have described in the Data Appendix. The authors retrieve the data from the Global Financial data, while we combine the data from the OECD and Datastream (REFINITIV, Reuters), due to the unavailability of the first option. Either way, the only difference is in terms of the magnitude of the coefficient of household debt in the First Stage, which does not introduce significant changes in the interpretation of the results.

We still need to take additional precautions in terms of assuring the impact of the credit/debt variables on GDP. It is expected that there were other effects associated with the decrease of the interest rate spreads in peripheral Eurozone countries between 1996 and 1999 that also had an impact on GDP. That is, we need to consider that this decline in the real sovereign spreads could have influenced GDP growth through other variables, other than the 4 credit/debt variables. One possibility would be the consideration of other sectors. Our focus is on the private non-financial sector. It could be that some of the positive or negative impacts on GDP growth are connected to the borrowing or lending of other sectors, including the public sector, or the financial sector. For example, lower spreads could have led to productive investments by financial firms which would contribute to GDP growth in the long-term. Or could also have led to cheaper public borrowing which was allocated to unproductive investments and resulted in lower GDP growth.

Lastly, other possibilities include the misallocation of additional resources to lower productive sectors (this would be the point of view of [Charles et al., 2018], among others, which we discussed extensively in the Literature review). A significant number of non-financial firms in some peripheral Eurozone countries, like Portugal, for example, were found to have shifted the allocation of resources and investments from the tradable sector (more productive) to the non-tradable sector (less productive). This could indicate that the negative impact of the expansion of household debt on GDP growth may also have resulted from bad investment from the non-financial firm sector. However, in this case, we also take into account the effect through non-financial firm debt, and find that the impact is positive and statistically significant. Therefore, the impact would be contrary to the household debt increase. The example we have provided before could, then, be an exception, or simply be independent of the change in the real sovereign spread. A similar reasoning could be applied to the different impact between the 2 segments of the lending sector.

2.5.2 Interest Spreads: Mortgage Spread

We move to the usage of the spread between mortgage loans and the 10-year government bonds, the mortgage sovereign spread (spr^{MS}), as the instrument/credit supply shock of the 4 credit/debt variables, during the boom period of 2000. More specifically, we apply the decrease in this spread from 2000 to 2004 as our instrument z_i in equation 2.4, replacing the real sovereign spread, since this spread achieved one of the lowest values from 2003 to 2005 for most countries in our sample. The results are provided in Tables 2.8 and 2.9.

Table 2.8: Instrumental Variable: Mortgage Spread - Borrowing sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_{07-10}y_i$	$\Delta_{07-10}y_i$	$\Delta_{02-07}c_i^H$	$\Delta_{07-10}y_i$	$\Delta_{02-07}c_i^{NF}$	$\Delta_{07-10}y_i$	$\Delta_{07-10}y_i$	$\Delta_{07-10}y_i$
$\Delta_{00-04}spr_i^{MS}$			-6.4628**		-8.5450**			
			(0.4787)		(0.4877)			
$\Delta_{02-07}c_i^H$	-0.1028			-0.2252**			-0.4908*	-0.1857**
	(0.3818)			(0.0330)			(0.2106)	(0.0560)
$\Delta_{02-07}c_i^{NF}$		-0.1625				-0.1049**	0.0754	-0.1252**
		(0.1858)				(0.0226)	(0.0461)	(0.0389)
$\Delta_{02-07}y_i$							0.6838*	0.4290**
							(0.2809)	(0.0189)
Equation	OLS	OLS	FS	IV	FS	IV	IV	IV
First stage F-statistic			6.13		6.61			
R^2	0.0021	0.0214	0.1621	0.1608	0.2438	0.2426	0.6167	0.6537
Observations	37	37	37	37	37	37	37	37

Notes: This table reports instrumental variables regressions of GDP growth from 2007 to 2010 on the expansion in debt of the 2 segments of the borrowing sector: household debt to GDP from 2002 to 2007, and expansion of non-financial firm debt to GDP from 2002 and 2007. Columns 1 and 2 shows the OLS estimate for the similar model in columns 1 and 2 of Table 2.6, for the sample of countries for which the mortgage-sovereign spread variable is available. Columns 3-6 use the change in the mortgage spread over the 10-year government bond yield during 2000-2004 as an instrument for the increase in household or non-financial firm debt to GDP from 2002-2007. Column 7 adds described variables when we use household debt as the dependent variable in the First Stage, while column 8 adds described variables when we use non-financial firm debt as the dependent variable in the First Stage. Standard errors in parentheses are robust to heteroskedasticity. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table 2.9: Instrumental Variable: Mortgage Spread - Lending sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_{07-10}y_i$	$\Delta_{07-10}y_i$	$\Delta_{02-07}c_i^B$	$\Delta_{07-10}y_i$	$\Delta_{02-07}c_i^{MBF}$	$\Delta_{07-10}y_i$	$\Delta_{07-10}y_i$	$\Delta_{07-10}y_i$
$\Delta_{00-04}spr_i^{MS}$			-11.8777**		-1.0406**			
			(0.6419)		(0.1664)			
$\Delta_{02-07}c_i^B$	-0.1515			-0.1225**			-0.2972**	-0.0204
	(0.1845)			(0.0163)			(0.0165)	(0.0297)
$\Delta_{02-07}c_i^{MBF}$		-0.1809				-0.8613**	0.2179**	-0.1226
		(0.2352)				(0.2324)	(0.0224)	(0.1551)
$\Delta_{02-07}y_i$							0.8531**	0.2758**
							(0.0250)	(0.0156)
Equation	OLS	OLS	FS	IV	FS	IV	IV	IV
First stage F-statistic			13.26		0.57			
R^2	0.0170	0.0149	0.3081	0.3071	0.0232	0.0218	0.4199	0.0947
Observations	41	41	41	41	41	41	41	41

Notes: This table reports instrumental variables regressions of GDP growth from 2007 to 2010 on the expansion in credit of the 2 segments of the lending sector: bank credit to GDP from 2002 to 2007, and market based finance to GDP from 2002 and 2007. Columns 1 and 2 shows the OLS estimate for the similar model in columns 1 and 2 of Table 2.7, for the sample of countries for which the mortgage-sovereign spread variable is available. Columns 3-6 use the change in the mortgage spread over the 10-year government bond yield during 2000-2004 as an instrument for the increase in bank credit or market based finance to GDP from 2002-2007. Column 7 adds described variables when we use bank credit as the dependent variable in the First Stage, while column 8 adds described variables when we use market based finance as the dependent variable in the First Stage. Standard errors in parentheses are robust to heteroskedasticity. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

As before, the first 2 columns, and Figure 2.6 in the Appendix, present the OLS estimations, using only each of our 4 credit/debt variables as the independent variable. All of the estimated coefficients are negative, but also none are statistically significant. Although, when we shift to the IV regressions, all of them become statistically significant, albeit also being negative. In columns 3 and 5, or Figure 2.7, we have the first stage impact (the effect of our instrument, the mortgage sovereign spread, on each of the 4 credit variables), which is negative and statistically significant for all cases. In terms of the magnitude of the coefficients, it reveals a strong first stage impact for 3 of them, where the impact is lower for the market based finance. The fact that they are negative implies that lower mortgage spreads lead to higher increases in the debt/credit in all segments.

Again, this would point to a credit supply shock being the source of a significant expansion in credit/debt variables during the 2000s boom period. A credit demand shock would either not affect or even increase the mortgage spreads (for example, if there was a preference shock that led to higher borrowing). Although, there could also be demand shocks that lead to lower spreads (for example, higher income shocks). In this case, borrowers would have higher possibilities for repayment, leading to lower risks to the lender and, thus, lower costs/spreads charged. However, it would make sense that this would translate into a positive impact on GDP, which is not the case. As we can see in columns 4 and 6 (as well as 7 and 8), and in Figure 2.8, the drop in the mortgage spread led to a lower GDP growth between 2007 and 2010.

2.5.3 Interest Spreads: Corporate Spread

We now test for the possibility of the corporate spread (spr^{corp}) as our instrument, using all available data. [Krishnamurthy and Muir, 2017] show that GDP growth in period t is negatively correlated to corporate credit spreads, both in year t-1 and t-2. Their interpretation is also similar: a rise in credit supply leads to a subsequent fall, resulting in the negative impact towards GDP growth (although they focus on periods with low spreads, during financial crises). The results are shown in Tables 2.10 and 2.11. We begin with columns 1 and 2, which provide OLS estimates of the impact of each of the 4 credit/debt variables on the change in 1 year GDP growth, with and without the inclusion of the contemporaneous and lagged corporate spread as a regressor. As we can observe, the 2 segments of the borrowing sector, and the bank credit have a negative impact on the change in 1 year GDP growth, with the exception being the market based finance, which exerts a positive impact. All of them are statistically significant. The results we obtain in column 2 for Table 2.10 are consistent with the findings of [Krishnamurthy and Muir, 2017].

Table 2.10: Instrumental Variable: Corporate Spread - Borrowing sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_1 y_{it+1}$	$\Delta_1 y_{it+1}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$	$\Delta_3 c^H_{it-1}$	$\Delta_3 y_{it+3}$	$\Delta_3 c^{NF}_{it-1}$	$\Delta_3 y_{it+3}$
spr^{corp}_{it}		0.3544*		0.4716	-0.8823*		-1.0236	
		(0.1468)		(0.3317)	(0.3670)		(0.6761)	
spr^{corp}_{it-1}		-0.1643		-1.0363**				
		(0.1480)		(0.3247)				
$\Delta_3 c^H_{it-1}$	-0.1194**	-0.1031**	-0.2553**	-0.4249**		-1.8983*		
	(0.0422)	(0.0251)	(0.0286)	(0.0558)		(0.8425)		
$\Delta_3 c^{NF}_{it-1}$	-0.0184	-0.0198$^+$	0.0234$^+$	0.1271**				-0.2498
	(0.0216)	(0.0119)	(0.0139)	(0.0275)				(0.3604)
Equation	OLS	OLS	OLS	OLS	FS	IV	FS	IV
First stage F-statistic					5.78		2.29	
Country fixed effects	✓	✓	✓	✓				
Distributed lag in Δy	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.0807	0.1696	0.3051	0.4370	0.0356	0.0308	0.0121	0.0071
Observations	1,626	215	1,544	187	201	201	201	201

Notes: This table reports OLS and IV estimations using the corporate spread, spr^{corp}, as the instrument, or adding it to the regressions as an independent variable. The impact is assessed on the 1 year and 3 year change in GDP growth through the expansion in debt of the 2 segments of the borrowing sector: household debt to GDP and non-financial firm debt to GDP. Columns 1 to 4 show the OLS estimates, for the impact on the change of GDP growth in 1 year and 3 years. Columns 5-8 use the contemporaneous corporate spread as the instrument for the IV regressions. In columns 5 and 6, we use household debt as the dependent variable in the First Stage, while in columns 7 and 8, we use non-financial firm debt as the dependent variable in the First Stage. Standard errors in parentheses are robust to heteroskedasticity. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Table 2.11: Instrumental Variable: Corporate Spread - Lending sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_1 y_{it+1}$	$\Delta_1 y_{it+1}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$	$\Delta_3 c^B_{it-1}$	$\Delta_3 y_{it+3}$	$\Delta_3 c^{MBF}_{it-1}$	$\Delta_3 y_{it+3}$
spr^{corp}_{it}		0.0362		-0.4595	-1.1264*		-1.0362	
		(0.1931)		(0.5415)	(0.5418)		(0.8539)	
spr^{corp}_{it-1}		-0.0832		0.5448				
		(0.1916)		(0.5225)				
$\Delta_3 c^B_{it-1}$	-0.0426**	-0.0499**	-0.1579**	-0.1973**		-1.5119*		
	(0.0073)	(0.0168)	(0.0159)	(0.0547)		(0.6271)		
$\Delta_3 c^{MBF}_{it-1}$	0.0192**	0.0379*	0.0666**	0.1489**				-0.2650
	(0.0068)	(0.0148)	(0.0148)	(0.0469)				(0.4254)
Equation	OLS	OLS	OLS	OLS	FS	IV	FS	IV
First stage F-statistic					4.32		1.47	
Country fixed effects	✓	✓	✓	✓				
Distributed lag in Δy	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.2753	0.1852	0.3654	0.6066	0.0176	0.0126	0.0141	0.0091
Observations	1,626	215	1,544	186	201	201	201	201

Notes: This table reports OLS and IV estimations using the corporate spread, spr^{corp}, as the instrument, or adding it to the regressions as an independent variable. The impact is assessed on the 1 year and 3 year change in GDP growth through the expansion in credit of the 2 segments of the lending sector: bank credit to GDP and market based finance (MBF) to GDP. Columns 1 to 4 show the OLS estimates, for the impact on the change of GDP growth in 1 year and 3 years. Columns 5-8 use the contemporaneous corporate spread as the instrument for the IV regressions. In columns 5 and 6, we use bank credit as the dependent variable in the First Stage, while in columns 7 and 8, we use market based finance as the dependent variable in the First Stage. Standard errors in parentheses are robust to heteroskedasticity. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

When we shift towards the analysis of our usual effect on the subsequent GDP growth ($\Delta_3 y_{it+3}$), we see that the inclusion of the corporate spread maintains the direction, magnitude, and statistical significance of the effects of each of the 4 credit/debt variables. The household debt and bank credit have a negative effect, while non-financial firm debt and market based finance have a positive effect, re-iterating the findings of column 5 of Table 2.1. It would suggest that each of these impacts on subsequent GDP growth are not just a consequence of the large increase in corporate credit spreads related to the losses in unpaid loans in the banking sector and loss of revenues in the business sector, during the Great Financial crisis, and, thus, not just related to the crisis itself.

Regarding the corporate spread as a regressor itself, it is not statistically significant for the lending sector in neither of the scenarios, and in the borrowing sector, it seems to have a positive impact for the contemporaneous period, and a negative impact for the lagged period. However, they are not statistically significant in both cases, and the direction of their impact seems to be the opposite of the findings in [Mian et al., 2017a] (see their table 4 in the online Appendix). Thus, we are careful in not extrapolating additional information on these results.

In terms of the results from the IV regressions, we have the First Stage estimations in columns 5 and 7, as well as Figure 2.9 in the Appendix. All of the estimated coefficients are negative, implying that a lower corporate credit spread leads to higher debt/credit in each of the 4 variables. In the Second Stage, described in columns 6 and 8, and Figure 2.10 in the Appendix, it shows a negative impact for all variables as well. Both the First and Second Stage coefficients only seem to be statistically significant for the household debt and the bank credit.

Summing up, the analysis of all three interest spreads used point to the following mechanism: a positive credit supply shock (which is identified by lower spreads) boosts debt/credit to GDP ratio of all 4 variables. The subsequent effect on GDP growth (three or four years following this initial shock) will depend on the variable in question. For the bank credit and household debt, the effect is consistently negative and statistically significant. For the non-financial firm debt and the market based finance, the effect is more dubious. In some cases, the effect on subsequent GDP growth is positive (in the case of the corporate credit spread, and the real sovereign spread), while in others it is negative (in the case of the mortgage spread). One consistent element about the non-financial firm debt and the market based finance is given by the statistical significance of their coefficients. In terms of impact on subsequent GDP growth, the coefficients are usually statistically significant when they are positive, and are usually not statistically significant when they are negative.

2.5.4 Additional Instruments: Excess Bond Premium (EBP)

In this subsection, we begin adding other potential instruments to our list. The first instrument is the Excess Bond Premium (EBP). As we have previously exposed, this is a popular instrument that has been used as a proxy for credit supply shocks. This measure was initially established by [Gilchrist and Zakrajsek, 2012], and it captures the residual component of their credit spread index. This index, which the authors name "GZ", is simply calculated as the arithmetic average of the credit spreads on outstanding bonds in any given month. Then, they decompose this "GZ" spread into two components: the first one that encompasses the usual countercyclical movements in expected defaults (the predictive component), and the second one encompasses the cyclical changes in the relationship between measured default risk and credit spreads (the residual component), which corresponds to the excess bond premium (EBP). They explain that this decomposition and the focus on the residual component is related to the "credit spread puzzle", the well-established result from the corporate finance literature which shows that less than 50% of the variation in corporate bond credit spreads can be attributed to the financial health of the issuer (as demonstrated by [Elton et al., 2001]). According to many authors, including [Collin-Dufresne et al., 2001], [Houweling et al., 2005], and [Driessen, 2005], the remaining unexplained component of the variation in credit spreads can mainly be attributed to a default-risk element that encompasses a demand by investors of guarantees or compensation higher than the expected losses to the corporate credit risk. The remaining elements include time-varying liquidity premiums, or tax treatment of corporate bonds.

The results are presented in Table 2.12. We provide the IV estimations, using the lagged EBP as the instrument, on each of the 4 credit/debt variables. The First Stage results (which can also be assessed in Figure 2.11), show a negative impact of the lagged EBP on the credit/debt variables. This can be explained by a lower level of the EBP being associated with a lower cost of credit/borrowing. That is, a lower EBP would translate in lower additional funds required by investors to compensate for the losses associated with default risk of specific loans/borrowers. It is likely that this requirement rises in periods of crisis, where there is a flight for safer assets due to the risks associated with defaults soaring, and investors would demand more resources to cover beyond expected losses. Thus, a lower EBP translates into higher credit/debt. Even though this effect is statistically significant (except for bank credit), it is only significant at 10%, due to high levels of standard deviations. This could be connected to the lower number of observations of the EBP instruments in our sample. The Second Stage impact on the subsequent GDP growth is also negative, across all the 4 credit/debt variables. However, they are only statistically significant for the bank credit and the household debt, which matches our results so far.

Table 2.12: Instrumental Variable: Excess Bond Premium (EBP)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_3 c^B_{it-1}$	$\Delta_3 y_{it+3}$	$\Delta_3 c^{MBF}_{it-1}$	$\Delta_3 y_{it+3}$	$\Delta_3 c^H_{it-1}$	$\Delta_3 y_{it+3}$	$\Delta_3 c^{NF}_{it-1}$	$\Delta_3 y_{it+3}$
EBP_{it-1}	-1.4424		-2.9188$^+$		-2.0269$^+$		-2.8548$^+$	
	(1.1033)		(1.5902)		(1.1522)		(1.6056)	
$\Delta_3 c^B_{it-1}$		-1.1541$^+$						
		(0.6864)						
$\Delta_3 c^{MBF}_{it-1}$				-0.4855				
				(0.8364)				
$\Delta_3 c^H_{it-1}$						-0.8213$^+$		
						(0.4807)		
$\Delta_3 c^{NF}_{it-1}$								-0.4964
								(0.8132)
Equation	FS	IV	FS	IV	FS	IV	FS	IV
First stage F-statistic	1.71		3.37		3.09		3.16	
R^2	0.0178	0.0071	0.0339	0.0232	0.0361	0.0257	0.0378	0.0272
Observations	94	94	94	94	94	94	94	94

Notes: This table reports IV estimations using the Excess Bond Premium (EBP), as the instrument. The impact is assessed on the 3-year change in GDP growth through the expansion in credit/debt of the 2 segments of the lending sector: bank credit to GDP and market based finance (MBF) to GDP, and the 2 segments of the borrowing sector: household debt and non-financial firm debt to GDP. Columns 1-4 use the lagged EBP as the instrument for the IV regressions, for the lending sector, while columns 5-8 use it for the borrowing sector. Standard errors in parentheses are robust to heteroskedasticity. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

2.5.5 Additional Instruments: Financial Conditions Index (FCI)

We also add the Financial Conditions Index (FCI) as a possible instrument. We take the data provided in the IMF Global Financial Stability Report in 2017. Then, we complement with data provided by Bloomberg, for the more recent years. This index is estimated on a monthly frequency, for 43 advanced and emerging market economies, using a set of 10 main financial indicators. These main financial indicators include corporate spreads, term spreads, interbank spreads, sovereign spreads, the change in long-term interest rates, equity return, house price returns, equity return volatility, the change in the market share of the financial sector, and credit growth. The remaining financial indicators include variables that summarize global risk sentiment (Chicago Board Options Exchange Volatility Index [VIX], Merrill Lynch Option Volatility Estimate [MOVE] Index), credit aggregates that directly indicate the level of financial vulnerability in the economy, and commodity prices and exchange rates which may influence and reflect the ease of funding and financial constraints (for example, by changing borrowers net worth)[7]. The IMF also includes additional variables for some of the countries in their dataset, when available, for robustness check purposes. For example, for the US, the calculations also added the lending standards, as an additional variable, and the estimated results for the FCI were fairly similar.

In terms of the IMF methodology, they follow the one applied by [Koop and Korobilis, 2014][8], and builds on the contribution of [Primiceri, 2005] for VAR (Vector AutoRegressive) models with time-varying parameters, as well as on the contribution of [Doz et al., 2011] for dynamic factor models. The main advantages of this procedure are the following: 1 - it is able to control for current macroeconomic conditions; and 2 - it enables the connection between the financial conditions index (FCI) and macroeconomic conditions to be dynamic, that is, to change over time (due to the time-varying parameter component). In terms of the advantages of using this index, it includes that it is a univariate (single variable) indicator, becoming more parsimonious, while including relevant information from several different financial indicators. For sure, the possible downside is the loss of relevant information when aggregating the different indicators, especially by combining with more volatile indicators. For example, it is expected that asset prices and risk spreads may encompass higher volatility, and by combining them with the remaining variables, it may lead them to influence a lot of the behaviour of the FCI, and, by default, reduce the impact of the remaining variables, like the credit aggregates, which may incorporate risks of a long-term nature. Indeed, financial indicators are usually classified into two types, according to their higher impact on the short-term, or the long-term. Nevertheless, the

[7]The main reason for the inclusion of these additional financial indicators is that, with the exception of a small number of the advanced countries, the developments in asset prices are not likely to encompass the relevant information with respect to the vulnerabilities contained in the financial aggregates. Therefore, using the information of the aggregates directly may improve the accuracy of the index.

[8]More detailed information on the Matlab code used can be found at:
https://sites.google.com/site/dimitriskorobilis/matlab

evolution of these two types is not independent (more detail is provided by [Krishnamurthy and Muir, 2017]). For example, the growth in the aggregates (with a higher impact on the long term), may cause a change in market expectations on different risks. This could lead to a tightening of spreads, with higher impacts on the risks of economic growth in the short-term.

In terms of our results, they are shown in Table 2.13. As before, the table displays the IV regression estimations, where the lagged FCI is used as the instrument for each of the 4 credit/debt variables, and the effect is assessed on subsequent changes in GDP growth. For the First Stage (which can also be seen in Figure 2.12 in the Appendix), the impact is always positive, across the 4 different debt/credit variables. This is expected, as a higher financial conditions index would imply more favourable financial conditions, from the overall financial conditions' variables taken into account by the index. Thus, a higher financial conditions index would translate into more credit granted, and higher amounts of debt borrowed. As for the Second Stage impact, it is also positive, implying a positive effect on subsequent GDP growth. For the non-financial firm debt and the market based finance, this is consistent with the results that we obtained before. However, when we look into the bank credit and household debt, this is contradictory to the conclusions we have been taking so far. That is, that a credit shock that increases bank lending and/or household debt has a negative impact on subsequent GDP growth. One possible explanation for this outcome would be that the effect of bank credit and household debt on subsequent GDP would depend on the underlying nature of the credit supply shock itself. In the same way that there are good booms and bad booms, there are reasons to believe that there could be credit supply shocks that lead to an expansion in bank credit and/or household debt that have a positive influence on GDP growth, even though most would lead to a negative impact. As the FCI incorporates different financial and economic information, a positive FCI would point to overall good economic and financial circumstances, for the short term and the long term. Thus, we could interpret that there are solid conditions upon which the bank credit lent and the household debt borrowed are based would not reverse themselves in the future (for example, that the financial system is more resilient to any shocks), and are able to lead to a positive effect on GDP growth, instead of a possible reversal of these conditions, which would lead to the negative impact we have identified before. All these coefficients are statistically significant, with the exception of the market based finance.

Table 2.13: Instrumental Variable: Financial Conditions Index (FCI)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_3 c^{B}_{it-1}$	$\Delta_3 y_{it+3}$	$\Delta_3 c^{MBF}_{it-1}$	$\Delta_3 y_{it+3}$	$\Delta_3 c^{H}_{it-1}$	$\Delta_3 y_{it+3}$	$\Delta_3 c^{NF}_{it-1}$	$\Delta_3 y_{it+3}$
FCI_{it-1}	0.5981**		0.1775		0.4051**		0.9096**	
	(0.1858)		(0.1218)		(0.1170)		(0.2421)	
$\Delta_3 c^{B}_{it-1}$		4.0376**						
		(1.5168)						
$\Delta_3 c^{MBF}_{it-1}$				10.9312				
				(7.4692)				
$\Delta_3 c^{H}_{it-1}$						6.1508**		
						(2.2478)		
$\Delta_3 c^{NF}_{it-1}$								2.8378**
								(1.0459)
Equation	FS	IV	FS	IV	FS	IV	FS	IV
First stage F-statistic	10.36		2.26		11.99		14.12	
R^2	0.0196	0.0181	0.0034	0.0031	0.0127	0.0109	0.0241	0.0223
Observations	651	651	651	651	541	541	541	541

Notes: This table reports IV estimations using the Financial Conditions Index (FCI), as the instrument. The impact is assessed on the 3-year change in GDP growth through the expansion in credit/debt of the 2 segments of the lending sector: bank credit to GDP and market based finance (MBF) to GDP, and the 2 segments of the borrowing sector: household debt and non-financial firm debt to GDP. Columns 1-4 use the lagged FCI as the instrument for the IV regressions, for the lending sector, while columns 5-8 use it for the borrowing sector. Standard errors in parentheses are robust to heteroskedasticity. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

2.5.6 Additional Instruments: Principal Component Analysis (PCA)

In the final part of this section, we introduce the sixth and final instrument, the principal component analysis (PCA). Principal Component Analysis is a method applied for dimensionality reduction, that is, to reduce the dimension of very large datasets, by decreasing the number of variables in it, while still maintaining the vast majority of the information provided by the initial dataset. The benefit is connected to an easier visualization, exploration and analysis of the data (including through the use of machine learning algorithms), without having the downside of time consumption to process all the variables. Naturally, there is a trade-off to this simplification, which is the loss of information and lower accuracy of our final dataset. Thus, the main goal is to minimize the loss of accuracy while aiming for simplicity, that is, to reduce the number of variables while preserving as much information as possible.

More specifically, the principal components of a set of observations are a sequence of m unit vectors where the i-th vector is the direction of a line that best fits the data while being orthogonal to the first $i-1$ vectors. What we mean by 'best fit' is a line that minimizes the average squared distance from the points to the line. These directions constitute an orthonormal basis in which different individual dimensions of the data are linearly uncorrelated. When using this method, several principal components are calculated, where the first principal component of a set of n variables (assumed to be jointly normally distributed), corresponds to the derived variable that is constructed as a linear combination of the original variables that also explains the most overall variance. The second principal component corresponds to the variable that is constructed as a linear combination of the original variables that explains the most variance in what is left once the effect of the first component is removed. This method will continue calculating principal components through j iterations until all the variance is explained. This method is more beneficial the more correlated the variables in the original dataset are, since the range for reduction of the dataset is large, while the loss of information is kept low.

Our objective here is rather similar. Although we do not seek to reduce the number of variables in our dataset, we seek to use this method to, instead, combine all our 5 instruments into a single one, such that we are able to capture most of the information given by the instruments into a single variable, while minimizing the loss of information. Thus, we apply this method using the following steps: 1 - our original dataset would just comprise of the 5 previous instruments; 2 - we calculate the principal components, and obtain a total of 5 principal components; 3 - we use just the first and second principal components to construct our new instrument, using the amount of total variation explained of each component as the weights (the first explains around 56% of all the variation, while the second explains around 29% of all the variation, with a total of 85% of the total variation explained. We can, then, quantify the cost of loss of information at 15%). Therefore, the final instrument will be a weighted average of the first two principal components of the previous 5 instruments, using the explanatory power of each principal component as the weights.

In terms of the results obtained, we point towards Table 2.14. The main 2 differences between this scenario and the previous ones is that we are using the Principal Component Analysis (PCA) as the instrument for our 4 credit/debt variables. The second difference relates to also using all these credit/debt variables as regressors. In addition, we have also included the distributed lags in Δy. For the First Stage, the effect is positive for the lending sector, while being negative for the borrowing sector. It would imply that a higher value of the Principal Component Analysis (PCA) would lead to more lending, but also less borrowing. This would imply that, either the excess amount of lending would be allocated to foreign borrowers, or it would be an inconsistency. However, we can see that, in terms of statistical significance, the First Stage effects are more significant for the lending sector than for the borrowing sector (for household debt, it is not statistically significant, while for non-financial firm debt, it is only significant at 10%, while it is significant at 5% for bank credit and at 1% for market based finance), suggesting that the borrowing either decreases or is unaffected. For the Second Stage effects, the bank credit is consistently negative, with higher significance again for the lending sector, which is consistent with our previous results so far. For the market based finance, the impact on subsequent GDP growth is negative in most cases (the only exception being when the household debt is used as the dependent variable in the First Stage). However, the coefficients are only statistically significant when the effect is negative. For household debt, the impact on GDP growth switches between positive and negative. However, none of them are statistically significant. Not only that, when the household debt is used as the dependent variable in the First Stage, all coefficients in the First and Second stage are not statistically significant (see columns 5 and 6). For the non-financial firm debt, the impact on subsequent GDP growth is positive, with one exception, which is not statistically significant. In terms of statistical significance, overall, there is higher significance when the credit variables from the lending sector are used as dependent variables for the First Stage, instead of the borrowing sector variables. There is also significance volatility for most of the coefficients in the Second Stage, which may result from the influence of more volatile instruments used in the PCA estimation (for example, from the Financial Conditions Index (FCI)).

Table 2.14: Instrumental Variable: Principal Component Analysis (PCA)

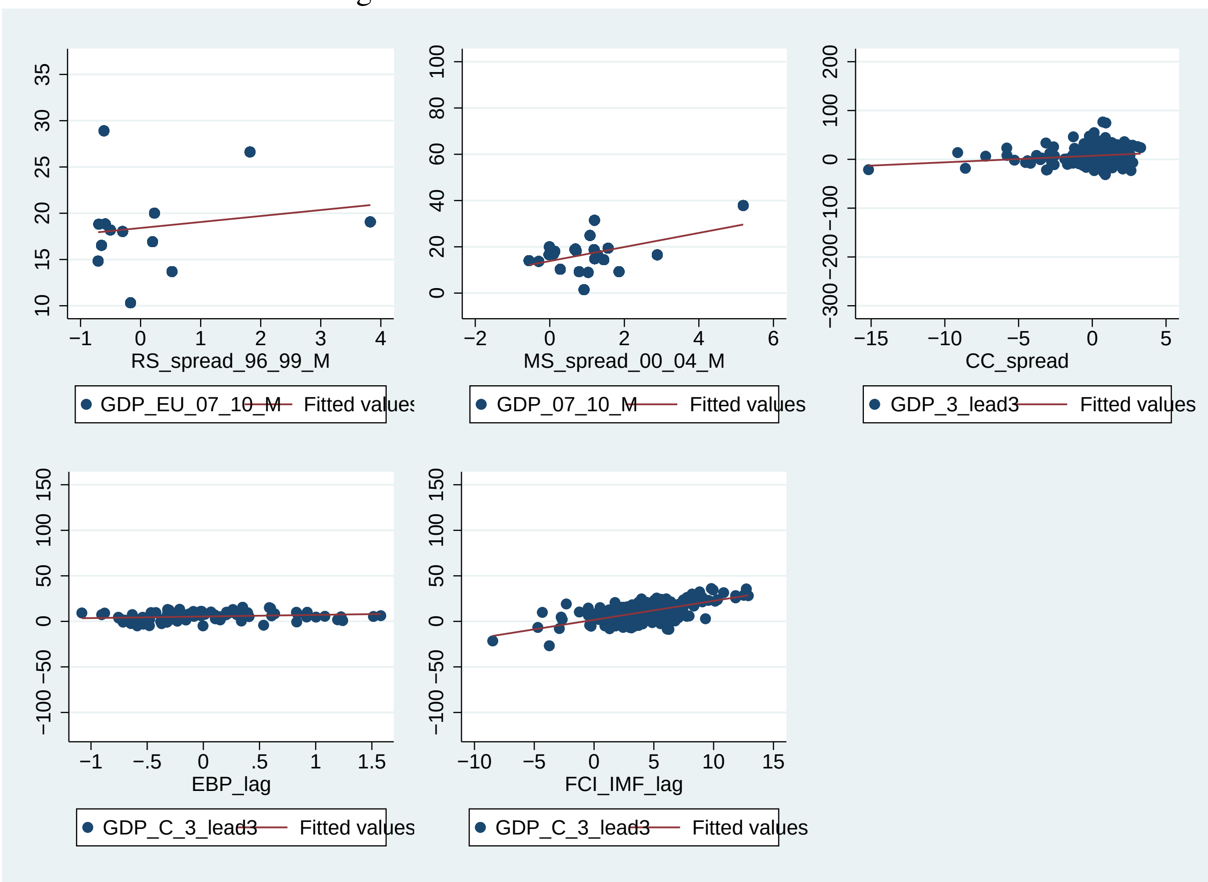
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_3 c^{B}_{it-1}$	$\Delta_3 y_{it+3}$	$\Delta_3 c^{MBF}_{it-1}$	$\Delta_3 y_{it+3}$	$\Delta_3 c^{H}_{it-1}$	$\Delta_3 y_{it+3}$	$\Delta_3 c^{NF}_{it-1}$	$\Delta_3 y_{it+3}$
PCA_{it}	2.1967*		3.8767**		-0.9032		-1.4214^{+}	
	(0.9493)		(0.8542)		(0.6171)		(0.7758)	
$\Delta_3 c^{B}_{it-1}$		-9.7216*		-2.2630**		-3.6141		-2.9320^{+}
		(4.2546)		(0.8840)		(2.6495)		(1.7371)
$\Delta_3 c^{MBF}_{it-1}$		-4.1589^{+}		-5.3327**		0.1398		-5.3013^{+}
		(2.2684)		(1.3866)		(0.9161)		(2.9450)
$\Delta_3 c^{H}_{it-1}$		6.2204^{+}		-0.0597		9.5194		-1.5302
		(3.6222)		(0.8850)		(6.6548)		(1.1735)
$\Delta_3 c^{NF}_{it-1}$		4.0253^{+}		3.8001**		-1.0284		6.1889^{+}
		(2.1308)		(1.1560)		(0.9854)		(3.3596)
Equation	FS	IV	FS	IV	FS	IV	FS	IV
First stage F-statistic	52.71		43.99		62.11		9.54	
Distributed lag in Δy	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.5678	0.5644	0.6477	0.6449	0.4504	0.4460	0.7192	0.7160
Observations	1,035	1,035	1,035	1,035	1,035	1,035	1,035	1,035

Notes: This table reports IV estimations using the Principal Component Analysis (PCA), as the instrument. The impact is assessed on the 3-year change in GDP growth through the expansion in credit/debt of the 2 segments of the lending sector: bank credit to GDP and market based finance (MBF) to GDP, and the 2 segments of the borrowing sector: household debt and non-financial firm debt to GDP. Columns 1, 3, 5 and 7 report the results for the First Stage, when we use the PCA as the instrument for the IV regressions, while the remaining columns reflect the results for the Second Stage estimations. Standard errors in parentheses are robust to heteroskedasticity. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

Finally, we provide the reduced form relationship between each of the 5 instruments and subsequent GDP growth. We have excluded the PCA instrument, since it is a combination of the 5 previous instruments. As we can see in Figure 2.1, all instruments have a positive relationship with GDP growth, in their reduced form. These results are consistent with the ones found in [Mian et al., 2017a], for the first 2 instruments (the estimations for the reduced form of the corporate spread are not provided in their article). Notice that the reduced form effect of these instruments leads to the opposite conclusion to when they are used as an instrument (with the exception of the Financial Conditions Index (FCI)). In most cases, recall that the lower value of the instrument would lead to an increase of both borrowing and lending segments. But the effect of the increase in credit/debt would have a negative impact on subsequent GDP growth (mostly through bank credit and household debt). One possible explanation is that there were also cases where the expansion in credit/debt led to a positive influence on subsequent GDP growth (more specifically, through market based finance, and non-financial firm debt). Even though we find that some of these cases are not statistically significant, while almost all scenarios for the negative impact of bank credit and/or household debt on GDP growth are statistically significant, this aspect is not taken into account, when capturing the average reduced form impact. Another possibility is that the reduced form does not accurately captures the impact that each of these instruments have on subsequent GDP growth, leading to counterfactual results. Instead, the Instrumental Variable estimation, using each of these variables as instruments, leads to results confirmed by empirical data.

Summing up, adding our 3 additional instruments led to some consistencies with the previous instruments: 1 - the First Stage effects are also statistically significant; 2 - in most cases, the bank credit and household debt have a negative impact on subsequent GDP growth, and it is statistically significant, especially for the bank credit. Some of the main differences would be the positive impact on subsequent GDP of all 4 credit/debt variables, when we use the Financial Conditions Index (FCI) as the instrument. As we previously explained, this could be connected with the specific instrument, which aggregates different financial and economic variables, and could reflect sustainable conditions such that all 4 credit/debt variables have a positive effect on subsequent GDP growth. A final difference would be with higher volatility in our additional instruments, either in the First Stage or the Second Stage. This could be connected with lower restrictions on our sample when we use the additional instruments, either in terms of periods or number of countries.

Figure 2.1: All instruments - Reduced Form



Notes: This figure plots the relationship between the GDP growth and each of the 5 instruments. From top left to bottom right, we have Real Sovereign spread (RS_{spread}), then Mortgage spread (MS_{spread}), followed by Corporate Credit spread (CC_{spread}), Excess Bond Premium (EBP) and ending in FCI (Financial Conditions Index).

2.6 Rational or Biased Expectations?

In this section, we consider the possible effect of behavioural biases on each of the 4 credit/debt variables, and, subsequently, on economic growth. More specifically, we resort to the professional forecast data from the IMF World Economic Outlook (WEO) and from the OECD Economic Outlook publications. Data for 3 to 5 years ahead forecasts are provided since 1990, while data for 2 year ahead forecasts is provided since 1980, and 1 year ahead forecasts are provided since 1970.

We start with a direct analysis between 3 year ahead forecast of GDP growth and the change from 4 years ago to 1 year ago, in each of the credit/debt variables, which is provided in Figure 2.13. As we can see, there is an absence of a relationship (or potentially a small negative relationship) between the 2 variables, in all cases. In the case of the absence of a relationship, it implies that the change from 4 years ago to 1 year ago in each of the credit/debt variables is uncorrelated with the professional forecasts of GDP growth over the following 3 years. A negative relationship would imply that lowers levels of credit/debt from each of the variables would lead to higher expectations of subsequent GDP growth, and higher levels of credit/debt would lead to lower expectations of subsequent GDP growth.

When we plot the 3 year forecast error, which is defined as the difference between realized and forecasted growth, we obtain similar results, as can be observed in Figure 2.14. In this case, the negative relationship would imply that higher levels of the credit/debt variables are correlated with overoptimistic expectations of future GDP growth, that is, negative forecast errors. The negative relationship would be consistent for household debt and bank finance evidence that we found in Table 2.2.

However, recall that, according to Table 2.1, the market based finance and non-financial firm debt started having a positive impact on GDP growth for periods further ahead into the future. Indeed, this is also what we find in Figure 2.15 in the Appendix. We take the GDP forecast and forecast errors 5 years ahead into the future, and plot them against the change between 6 years and 1 year ago, for market based finance and non-financial firm debt. Indeed, we also find here a positive relationship, where a higher level of non-financial firm debt or market based finance (MBF) leads to a positive review of expectations, implying GDP growth was underestimated in these cases.

Table 2.15: Increase in credit/debt variables and relation with IMF and OECD GDP forecasts

	Growth Forecast					Forecast Error					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	$\Delta_1 y_{t+1\|t}$	$\Delta_2 y_{t+2\|t}$	$\Delta_3 y_{t+3\|t}$	$\Delta_4 y_{t+4\|t}$	$\Delta_5 y_{t+5\|t}$	$e_{t+1\|t}$	$e_{t+2\|t}$	$e_{t+3\|t}$	$e_{t+4\|t}$	$e_{t+5\|t}$	$e_{t+2\|t}$
$\Delta_3 c^B_{it-1}$	-0.0073**	-0.0044$^+$	-0.0021	-0.0021	-0.0104	0.0188**	-0.0307*	-0.0475**	-0.0755**	-0.0758**	-0.0557**
	(0.0026)	(0.0023)	(0.0021)	(0.0020)	(0.0064)	(0.0113)	(0.0151)	(0.0162)	(0.0158)	(0.0158)	(0.0156)
$\Delta_3 c^{MBF}_{it-1}$	-0.0012	-0.0014	0.0079*	0.0081*	0.0484**	0.0265**	0.0330*	0.0381*	-0.0001	0.0018	0.0156
	(0.0028)	(0.0025)	(0.0039)	(0.0037)	(0.0105)	(0.0069)	(0.0166)	(0.0171)	(0.0175)	(0.0174)	(0.0187)
$\Delta_3 c^H_{it-1}$	0.0010	0.0018	0.0036	-0.0003	-0.0068	0.0046	0.0296	0.0448*	0.0357$^+$	0.0367$^+$	-0.0267
	(0.0035)	(0.0031)	(0.0049)	(0.0026)	(0.0143)	(0.0089)	(0.0201)	(0.0213)	(0.0214)	(0.0213)	(0.0213)
$\Delta_3 c^{NF}_{it-1}$	0.0021	0.0009	-0.0041	0.0022	-0.0005	-0.0055	-0.0138	-0.0290$^+$	-0.0286$^+$	-0.0299$^+$	0.0104
	(0.0026)	(0.0023)	(0.0034)	(0.0020)	(0.0086)	(0.0062)	(0.0152)	(0.0158)	(0.0161)	(0.0160)	(0.0148)
Country Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sample	Full	Full	Full	Full	Full	Full	Full	Full	Full	Full	Pre2006
Test for equality (p-value):											
β_B and β_{MBF}	0.0259	0.2165	0.5747	0.6370	0.0000	0.2856	0.0001	0.0000	0.0000	0.0000	0.0016
β_H and β_{NF}	0.8145	0.8240	0.2893	0.4660	0.7617	0.3872	0.0902	0.0087	0.0211	0.0165	0.2307
R^2	0.0221	0.0190	0.0204	0.0226	0.0768	0.0290	0.0181	0.0401	0.0765	0.0782	0.0529
Observations	1,291	1,181	988	988	988	1,291	1,181	988	988	988	481

Notes: This table reports regression estimates of the change in each of the 4 credit/debt variables to GDP from t-4 to t-1 on the GDP growth forecasts and forecast errors, for different horizons. The forecasts are from the IMF World Economic Outlook and the OECD Economic Outlook (when IMF data is unavailable). $\Delta_h y_{t+h|t}$ corresponds to the forecasted change in log GDP from year t to t+h, made in year t, and $e_{t+h|t}$ is the realized forecast error. The IMF and OECD forecast errors are constructed using the realized log GDP change reported in the IMF's Historical WEO Forecasts Database and the OECD Economic Outlook reports, respectively. The regression in column 11 is estimated using data until 2006. Reported R^2 values are from within-country variation. Standard errors in parentheses are dually clustered on country and year. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

In Table 2.15, we also have these results. In columns 1-5, we have the correlation between each of the 4 credit/debt variables to GDP from t-4 to t-1 on the GDP growth forecasts, for different horizons (1 year ahead to 5 years ahead). The bank credit coefficient is consistently negative (implying higher bank credit leads to lower expectations of future GDP growth), but it is only statistically significant for the initial horizons. The market based finance is initially negative, but the impact turns positive for further horizons. Only the positive effects are significant. For household debt, the initial impact is positive, but then turns negative, matching the behaviour in Table 2.1, as is the case for the non-financial firm debt. However, neither of them are statistically significant for all horizons. The remaining information portrays the forecasting errors for different horizons (1 year ahead to 5 years ahead), where the last column excludes the years after 2006, to make sure the impact is not biased by the Great Financial Crisis. For the bank credit, all estimated coefficients are statistically significant, and it is the only one retaining significance when excluding the periods after 2006. The first impact is positive, while all the other ones are negative. This would imply that the effect of bank credit on GDP growth is initially underestimated (actual GDP growth is higher than expected), and then overestimated in most cases (actual GDP growth is lower than expected). The market based finance seems to be also underestimated in the initial periods, where it is statistically significant. This is also the case of household debt, where it seems to show some significance for later periods. As for the non-financial firm debt, the impact seems to be overestimated, especially for periods further in the future. The difference between the 2 coefficients, both for the lending and the borrowing sector is statistically significant for the forecasting errors, for all horizons.

We argue that our results are not consistent with rational expectations-based models, independently of being based on credit demand or credit supply shocks. Instead, it points to literature reflecting that market participants do not incorporate the negative effects of bank credit and/or household debt on GDP growth, which includes [Baron and Xiong, 2017] and [Fahlenbrach et al., 2018]. If this was not the case, we would not have the statistically significant relation between the credit/debt variables and the forecasting errors on GDP growth, especially for bank credit.

What about the source of the expectations errors? Do they result from the lending side (from the creditors) or the borrowing side (from the borrowers)? Our evidence from Table 2.15 would point to the mistakes being made by the lending side, especially the bank credit (since it is consistently statistically significant), although a small portion would also be made by the borrowing side. This would also be consistent with empirical evidence. As we explained before, in the case that it would be driven by the borrowers (for example, due to an increase in their optimism), and the credit supply remained constant, it would lead to higher interest rates charged, which is counterfactual with empirical data. Instead, [Bordalo et al., 2018] show that the forecasts by credit market analysts show signs of overoptimism in boom periods, when the spreads are low. This would point to the creditors being the ones that are more vulnerable to making forecasting errors when over-extrapolating the recent past.

Lastly, we consider additional possibilities and robustness tests, by considering other known predictors of GDP growth. This information is provided in Table 2.16. We begin by adding the three year change in general consumption to GDP ratio, and find that there is a negative impact, which is statistically significant. This would imply that increases in general consumption have a negative effect on subsequent GDP growth. When we isolate the durables segment from consumption, in column 2, the coefficient is also negative and statistically significant. However, its magnitude and significance decreases. This would imply that there is also a downward effect of the rise of durables consumption on GDP growth, but that most of the impact of the general consumption on GDP growth would be from the remaining segments, the consumption on non-durables and services[9]. In column 3, we consider the influence of residential investment to GDP ratio, but it is not statistically significant, implying that likely it is not relevant to explain the changes in GDP growth in the next 3 years.

In column 4, we also consider the impact of the real exchange rates. The coefficient shows to be statistically significant, and exert a negative impact on future GDP growth (although the magnitude is small). This would imply that an appreciation of the real exchange rate would generate lower subsequent GDP growth. In terms of the 4 credit/debt variables, both the household debt and bank credit coefficients are negative and statistically significant for all the different scenarios. This would point to a high connection between each of these segments of the lending and borrowing sector. It would imply that most of the negative effect on GDP growth results from the lending of the banking sector to the households. And even though that most of that debt is allocated to housing (falling under the consumption of durables segment), and that it also has a negative impact, the vast majority of the negative impact is from the consumption of non-durables or services.

In addition, given that both bank credit and household debt retain their significance after each of these scenarios, it implies that their predictive power does not simply reflect consumption booms, or real exchange rate appreciations. It also provides further evidence that a change in household beliefs is not enough to explain the negative effects of bank credit and household debt on economic growth. Thus, it points even further for the necessity of a change of beliefs on the side of the lender/creditor. For market based finance (MBF) and non-financial firm debt, only some of the coefficients are statistically significant, and have a positive impact on GDP growth.

If we isolate the lending sector, the market based finance (MBF) shows to be significant in almost all scenarios of Table 2.16 (with the exception of the real exchange rate scenario). For Table 2.15, the market based finance also becomes statistically significant for all the different scenarios. When we isolate the borrowing sector, there is an increase of the household debt sector statistical significance on Table 2.15, with a negative impact on GDP growth, with little

[9]We also consider the consumption on durables segment to GDP ratio as a robustness test, due to the results found by [Rognlie et al., 2018] on the relevance of the build-up consumption on durables in explaining the severity of the Great Financial Crisis.

impact on non-financial firm debt. For Table 2.16, the results are similar for the household debt, and there is higher significance for the non-financial firm debt, with a positive impact on GDP growth.

Table 2.16: Alternative Hypotheses and Robustness to Other Known Predictors of GDP Growth

	Consumption or Residential Investment Booms			Real Exchange Rate	Time Trends
	(1)	(2)	(3)	(4)	(5)
	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$
$\Delta_3 c^B_{it-1}$	-0.1747**	-0.0947**	-0.1895**	-0.1811**	-0.1441**
	(0.0252)	(0.0334)	(0.0254)	(0.0254)	(0.0223)
$\Delta_3 c^{MBF}_{it-1}$	0.0376	0.0613$^+$	-0.0037	0.0126	0.0496*
	(0.0263)	(0.0333)	(0.0286)	(0.0274)	(0.0248)
$\Delta_3 c^H_{it-1}$	-0.0911**	-0.1335**	-0.1177**	-0.0823*	-0.1164**
	(0.0336)	(0.0432)	(0.0339)	(0.0327)	(0.0300)
$\Delta_3 c^{NF}_{it-1}$	0.0148	0.0027	0.0718**	0.0489*	0.0059
	(0.0236)	(0.0301)	(0.0236)	(0.0249)	(0.0204)
$\Delta_3(C/Y)_{it-1}$	-3.4705**				
	(1.2418)				
$\Delta_3(C^{dur}/Y)_{it-1}$		-0.1919$^+$			
		(0.1049)			
$\Delta_3(I^{res}/Y)_{it-1}$			0.1993		
			(2.2734)		
$\Delta_3 reer_{it-1}$				-0.0444*	
				(0.0197)	
Country Fixed Effects	✓	✓	✓	✓	✓
Distributed Lags in Δy	✓	✓	✓	✓	✓
Country-specific Time Trends					✓
R^2	0.3565	0.5482	0.4856	0.5026	0.5497
Observations	1,005	657	901	721	1,005

Notes: This table reports robustness to controlling for other known predictors of GDP growth in the main single equation specification. Columns 1-3 control for the change in the consumption to GDP ratio, the change in the durable consumption to GDP ratio, and the change in the residential investment to GDP ratio from t-4 to t-1, respectively. Column 4 includes the change in the log real effective exchange rate from t-4 to t-1. The real effective exchange rate is from the BIS's "Effective exchange rate indices" dataset. Column 5 controls for country-specific time trends. All columns include country fixed effects and three lags of GDP growth (Δy_{it-1}, Δy_{it-2}, and Δy_{it-3}). Reported R^2 values are from within-country variation. Standard errors in parentheses are dually clustered on country and year. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

2.7 The Role of Macroeconomic Frictions

In this section, we explore the possible interaction between macroeconomic frictions, credit/debt and economic growth. The main reason is connected to the findings in theoretical literature, which shows that, for example, the negative impact of high levels of household debt on future economic growth is connected to macroeconomic frictions, including constraints on monetary policy or nominal rigidities.

2.7.1 Non-linearity

We begin with the connection between macroeconomic frictions and lower demand. In many theoretical models, where these frictions play a relevant role, it is usually assumed that a decrease in demand is needed to trigger frictions, which, then, leads to a fall in GDP. For example, a large decline in demand could require a significant reduction in interest rates (to achieve equilibrium), which raises the probability of binding monetary policy constraints (for example, the zero lower bound on nominal interest rates). Another possibility is offered by [Schmitt-Grohé and Uribe, 2016], as we explained previously, related to wage rigidities, and combining with non-linearities (wage rigidities were more relevant when wages fell than when they grew). The same non-linearity characteristic may also apply to bank credit and household debt. For example, it may be the case that a rise in bank credit and/or household debt leads to lower economic growth in latter periods (as we have found so far). But a decrease in household debt and/or bank credit may not lead to an increase in future GDP growth.

We start by evaluating this possibility in Table 2.17. Column 1 incorporates non-linearities, by subdividing the dataset between positive and negative values of each credit/debt to GDP variables. Columns 2-4 reflects separate estimations according to different exchange rate regimes in year t as reported by [Ilzetzki et al., 2019]. We use the "coarse" classification codes, which range from 1 to 6. We define "Fixed regimes" as arrangements with a coarse classification code equal to 1 (no separate legal tender, currency boards, pegs, and a pre-announced horizontal band that is narrower than or equal to $\pm 2\%$). "Intermediate regimes" are defined as arrangements with a classification code of 2 or 3 (crawling pegs, crawling bands, managed floating, moving bands, etc.). The remaining categories are classified as "Freely Floating", which would be the arrangements with a coarse classification code equal to 4 or 5. The classification of 6 is for missing data. We exclude 11 country-years in which the de facto arrangement is classified as “freely falling" (cases where 12-month inflation is greater than 40%).

Table 2.17: Non-linearity and Heterogeneity across Exchange Rate Regimes

	Non-linearity	Fixed	Intermediate	Freely Floating
	(1)	(2)	(3)	(4)
	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$
$\Delta_3 c^B_{it-1} * \mathbf{1}(\Delta_3 c^B_{it-1} > 0)$	-0.5345**			
	(0.1603)			
$\Delta_3 c^B_{it-1} * \mathbf{1}(\Delta_3 c^B_{it-1} \leq 0)$	-0.010			
	(0.2329)			
$\Delta_3 c^{MBF}_{it-1} * \mathbf{1}(\Delta_3 c^{MBF}_{it-1} > 0)$	0.0457*			
	(0.0200)			
$\Delta_3 c^{MBF}_{it-1} * \mathbf{1}(\Delta_3 c^{MBF}_{it-1} \leq 0)$	-0.2296			
	(0.2967)			
$\Delta_3 c^H_{it-1} * \mathbf{1}(\Delta_3 c^H_{it-1} > 0)$	-0.1767**			
	(0.0417)			
$\Delta_3 c^H_{it-1} * \mathbf{1}(\Delta_3 c^H_{it-1} \leq 0)$	0.0293			
	(0.4152)			
$\Delta_3 c^{NF}_{it-1} * \mathbf{1}(\Delta_3 c^{NF}_{it-1} > 0)$	0.0759			
	(0.0100)			
$\Delta_3 c^{NF}_{it-1} * \mathbf{1}(\Delta_3 c^{NF}_{it-1} \leq 0)$	0.6046			
	(0.8176)			
$\Delta_3 c^B_{it-1}$		-0.2493**	-0.1382**	0.6883
		(0.0747)	(0.0374)	(1.2020)
$\Delta_3 c^{MBF}_{it-1}$		0.1657*	-0.0257	0.7017
		(0.0825)	(0.0386)	(1.2267)
$\Delta_3 c^H_{it-1}$		-0.0203	-0.2086**	-0.7384
		(0.1165)	(0.0486)	(1.2090)
$\Delta_3 c^{NF}_{it-1}$		-0.0459	0.1001**	-0.7155
		(0.0702)	(0.0314)	(1.2186)
Country Fixed Effects	✓	✓	✓	✓
Distributed Lags in Δy	✓	✓	✓	✓
Test for equality (p-value):				
β_B and β_{MBF}		0.0000	0.0161	0.8864
β_H and β_{NF}		0.8614	0.0000	0.8224
R^2	0.1755	0.4246	0.4805	0.0729
Observations	728	333	498	204

Notes: All regressions include country fixed effects and three lags of GDP growth. Reported R^2 values are from within-country variation. Standard errors in parentheses are dually clustered on country and year. +,*,** indicates a significance at the 0.1, 0.05, 0.01 level, respectively. More detail is provided in subsection 2.7.1

Column 1 of Table 2.17 shows the results from the non-linear component. As we can see, we have subdivided our sample according to indicator variables for whether the country has experienced an increase or decrease in each of the 4 credit/debt variables, and then have them interact with our standard three-year change in each credit/debt variables. For the bank credit and the household debt, we can witness the presence of the non-linear component, where the predictive power on future economic growth results from situations where there is an increase in bank credit or household debt, respectively, but not when there is a decrease. This would imply that a rise in either bank credit or household debt would lead to a lower subsequent GDP growth, but a fall in either household debt or bank credit does not lead to a rise in future GDP growth. As for the market based finance, it also shows non-linear effects, but in the opposite direction. That is, a decrease in market based finance does not lead to a fall in future GDP growth, but higher market based finance results in a rise of subsequent economic growth. For non-financial firm debt, there is no significant impact in either direction.

2.7.2 Heterogeneity across exchange rate regimes

In this subsection, we explore the remaining information of Table 2.17. It relates to nominal rigidities connected to monetary policy constraints, which we identify through differences in exchange rate regimes. We divide the sample according to fixed, intermediate and freely-floating exchange rate regimes using the de facto classification from [Ilzetzki et al., 2019]. The presence of these constraints is clearly relevant for the lending sector, especially for bank credit. We can see that the coefficient is negative and statistically significant at 1% for both fixed and intermediate exchange rate regimes. But there is a decrease in magnitude when going from fixed to intermediate, and then becomes statistically insignificant for the freely floating regimes. For the market based finance, it is positive and significant for fixed exchange rate regimes, leading to a rise in future economic growth. For the borrowing sector, we only find significance for the intermediate exchange rate regime, which contrasts with the findings of [Mian et al., 2017a], where the behaviour of household debt is similar to what we found for the bank credit. However, when we isolate the regression for the borrowing sector, we find similar results to this article. We can conclude, then, that part of the significance captured in the fixed exchange rate regimes is due to the non-inclusion of the bank lending, and the constraint is relevant for the bank credit segment of the lending sector, and not exactly to the household debt segment of the borrowing sector. When isolating the lending sector, we also find that the market based finance (MBF) is significant in all scenarios, implying there is higher significance for this variable, but it is not affected by these constraints on monetary policy. The difference between the coefficients within the lending and borrowing sector are significant in the cases we find significance for the individual credit/debt variables (that is, the difference within the segments of the lending sector is significant for the fixed and intermediate exchange rate regimes, while the difference within the segments of the borrowing sector is significant for the intermediate exchange rate regimes).

2.7.3 Unemployment

In this subsection, we explore the macroeconomic frictions connected to wage rigidities, which we mentioned at the beginning of this section. We do this through the means of evaluating whether each of the credit/debt variables have an influence on unemployment. For example, in the case of wage rigidities, there is an expected rise in unemployment after an increase in household debt. The results are shown in Table 2.18. Our dependent variable is now the change in the following 3 years of the unemployment rate, instead of GDP growth for the same period. In column 1, all coefficients are positive, but only the lending sector coefficients are statistically significant. However, in terms of their magnitude, the values are not very large.

In column 2, we add the changes in the unemployment rate from the previous periods, as a measure of robustness to our initial results. In this case, the market based finance (MBF) ceases to be significant, while the household debt coefficient becomes statistically significant. The bank credit maintains its significance[10]. In fixed exchange rate regimes, all coefficients are statistically significant, especially the bank credit and the non-financial firm debt, with a positive impact. The market based finance and the household debt have a negative impact, although they are less significant. In the intermediate exchange rate regime, only the household debt coefficient is statistically significant, with a positive impact on the change in the unemployment rate. The evidence from columns 3 to 5 corroborates the evidence of Table 2.17, in which monetary policy flexibility is relevant for adjustments in the economy.

Finally, although we find some similarities with the results obtained by [Mian et al., 2017a], we also find some differences. In their case, the household debt is constantly statistically significant, with a positive impact on the unemployment rate, and so is the non-financial firm debt, for the scenarios throughout columns 1 to 4. But if we isolate the elements of the borrowing sector, we obtain similar results. When we just focus on the borrowing sector, the household debt is significant for the first 4 columns, while the non-financial firm debt is significant for the first 3 columns, both with positive impact. In terms of magnitude, it is similar to the bank credit. When we just focus on the lending sector, the bank credit coefficient is also significant in the intermediate exchange rate regimes, while there is no relevant change in the market based finance (MBF). The magnitude of the estimations is similar.

[10]Our results are also robust to using only subsample of OECD harmonized unemployment rate data, which are more internationally comparable than the series collected using different methodologies.

Table 2.18: Unemployment and Debt/Credit Expansions

	Full Sample		Fixed	Intermediate	Freely Floating
	(1)	(2)	(3)	(4)	(5)
	$\Delta_3 u_{it+3}$	$\Delta_3 u_{it+3}$	$\Delta_3 u_{it+3}$	$\Delta_3 u_{it+3}$	$\Delta_3 u_{it+3}$
$\Delta_3 c^{B}_{it-1}$	0.0437**	0.016**	0.0278**	0.0061	-0.2099
	(0.0095)	(0.0038)	(0.0065)	(0.0063)	(0.3469)
$\Delta_3 c^{MBF}_{it-1}$	0.0331**	-0.0039	-0.0125^{+}	0.0024	-0.2252
	(0.0102)	(0.0041)	(0.0067)	(0.0066)	(0.3479)
$\Delta_3 c^{H}_{it-1}$	0.0029	0.0106*	-0.0202*	0.0172*	0.2288
	(0.0131)	(0.0052)	(0.0102)	(0.0083)	(0.3463)
$\Delta_3 c^{NF}_{it-1}$	0.0107	0.0033	0.0164**	0.0008	0.2314
	(0.0091)	(0.0037)	(0.0061)	(0.0055)	(0.3494)
Country Fixed Effects	✓	✓	✓	✓	✓
Distributed Lags in Δu		✓	✓	✓	✓
Test for equality (p-value):					
β_B and β_{MBF}	0.3199	0.0000	0.0000	0.2974	0.3118
β_H and β_{NF}	0.6403	0.2886	0.0049	0.9734	0.8615
R^2	0.1200	0.8392	0.9201	0.8452	0.8700
Observations	1,173	1,166	361	528	206

Notes: This table reports regression estimates of the change in the unemployment rate from t to t+3 on the change in the 4 credit/debt to GDP from t-4 to t-1. All columns include country fixed effects. Columns 2-5 include three lags of the change in the unemployment rate as controls. Columns 3-5 estimate the regression across exchange rate regimes, as defined in Table 2.17. Reported R^2 values are from within-country variation. Standard errors in parentheses are dually clustered on country and year. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

2.8 House Prices and Other Predictors of Growth

As we pointed out in subsection 2.2.6, there is extensive literature that explores the connection between house prices and different sources of credit shocks, including different credit/debt variables, whether theoretical and/or empirical. In most cases, this connection is explored for the case of household debt, given the intrinsic connection between the 2 variables (since most of household debt is allocated to housing, it is expected to have an impact on house prices).

The results are reflected in Table 2.19. In the first 4 columns, we isolate each of our credit/debt variables, and evaluate their impact on house prices. More specifically, on the average real house price growth in the previous three years for each country. All of them are positive and statistically significant, at a 1% significance level. And, as expected, the household debt coefficient is the highest, with a rise of 2.58 units in house prices for each unit increase in household debt.

Again, we need to consider possible alternatives for the correlation between house prices and the debt/credit variables, and subsequent economic growth. That is, other independent shocks to house prices are what may cause the correlation between the credit/debt variables (for example, in household debt) and future GDP growth. The main possible shock is a change in the beliefs of house price growth in the future. In that scenario, agents become more optimistic for a rise in house prices, pushing for higher demand for credit, as well as for mortgages. This would imply a positive correlation between mortgage spreads (which would feel pressure to increase under higher housing demand), and changes in household debt, for example, which is counterfactual. Instead, to find negative correlation between household debt and mortgage spreads, the change in beliefs would have to result from their volatility, or downside risk. This information corresponds to assessments on default risk on mortgages, which, in the vast majority of cases, is evaluated by lenders, and not borrowers. Thus, even this possible change of beliefs could be considered as the source for the credit supply shock.

Table 2.19: House Prices, Debt/Credit, and GDP Growth

	$\Delta_3 ln(P^{Housing}_{it-1})$				$\Delta_3 y_{it+3}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_3 c^{B}_{it-1}$	0.9400**				-0.1596*	-0.1719**	-0.1477**	-0.1557*
	(0.0766)				(0.0691)	(0.0251)	(0.0311)	(0.0716)
$\Delta_3 c^{MBF}_{it-1}$		0.3174**			0.1113	0.0302	0.0159	0.0714
		(0.0802)			(0.0787)	(0.0278)	(0.0339)	(0.0801)
$\Delta_3 c^{H}_{it-1}$			2.5751**		-0.3620**	-0.1337**	-0.1725**	-0.4003**
			(0.0984)		(0.1079)	(0.0376)	(0.0454)	(0.1071)
$\Delta_3 c^{NF}_{it-1}$				0.9304**	-0.0581	0.0210	0.0476^{+}	-0.0975
				(0.0559)	(0.0696)	(0.0240)	(0.0269)	(0.0702)
$\Delta_3 ln(P^{Housing}_{it-1})$					0.0669**	0.0140^{+}	0.0031	0.0862**
					(0.0218)	(0.0078)	(0.0082)	(0.0225)
Country Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Distributed Lags in Δy						✓	✓	✓
Year Fixed Effects								✓
Sample	Full	Full	Full	Full	Full	Full	Pre2006	Full
Test for equality (p-value):								
β_B and β_{MBF}					0.0007	0.0000	0.0001	0.0044
β_H and β_{NF}					0.0179	0.0004	0.0001	0.0169
R^2	0.2054	0.1187	0.4201	0.2702	0.0909	0.1263	0.2360	0.6176
Observations	1,290	1,290	1,316	1,298	1,079	1,035	599	1,035

Notes: This table shows the correlation between each of the 4 credit/debt variables and house prices. Then, we include the house price growth in the main specification for GDP growth. Column 1-4 shows the correlation between the increase in each of the credit/debt variables to GDP and real house price growth over t-4 to t-1. Real house price growth is constructed from the BIS's "Long series on nominal residential property prices" (fourth quarter value) deflated by the CPI. Columns 5-8 report results from robustness checks that include the change in real house prices from t-4 to t-1 in the main specification. Columns 6-8 control for three GDP growth lags. All columns include country fixed effects, and column 8 also includes year fixed effects. Reported R^2 values are from within-country variation. Standard errors in parentheses are dually clustered on country and year. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

We address this point in the remaining columns of Table 2.19, in which we add the lagged change in house price growth as a regressor for our main condition. Both the bank credit and household debt are statistically significant for all the different scenarios, and yield a negative impact on future economic growth. It also shows that the negative impact on GDP growth of both these variables is not due to the house prices, making them a more robust predictor for this effect. Not only is the lagged house price growth not statistically significant in all the scenarios (see column 7), but it also has an unexpected positive impact on subsequent GDP growth in our sample, for all the different scenarios. When we isolate the lending sector, the market based finance (MBF) becomes statistically significant in almost all the scenarios, with a positive effect on future economic growth. When isolating the borrowing sector, the results are similar.

What about other potential predictors, besides house prices? One possibility is the real exchange rate overvaluations. According to [Gourinchas and Obstfeld, 2012], a real exchange appreciation (or, more specifically, a real exchange rate overvaluation) is a robust predictor of financial crises and lower economic growth. Indeed, if we go back to our column 4 of Table 2.16, we find that the appreciation of the exchange rate as a negative impact on subsequent GDP growth, and that it is statistically significant. Although, we also can see that the household debt and bank credit still remain statistically significant, even when including the lagged three-year change in the exchange rate as a regressor. Also, the magnitude is much lower than the other coefficients (half of household debt, and just 25% of bank credit).

2.9 Global Credit/Debt Cycle

2.9.1 Debt/Credit and External Adjustment

In this section, we make a more detailed analysis between our debt/credit variables, and the external sector. If we look into the information displayed in columns 1-4 of Table 2.20, it is not completely clear whether a rise of bank credit leads to an increase or a decrease of next exports relative to initial GDP[11]. We can see that the main reason is in columns 3 and 4 (impact on exports and imports, respectively), where higher bank credit results in lower imports and exports, which leads to an ambiguous effect on net exports in column 1 (the effect is positive, but very low and not statistically significant). Although column 2 shows that there seems to be a higher increase in exports than imports, the statistical significance is low, for which further analysis should and will be provide later on. When we shift the analysis to higher levels of market based finance, we can see that it predicts a worsening of net exports. That is, column 1 shows a negative and statistical significant influence of a rise in market based finance (MBF) on net exports relative to initial GDP. Column 3 reflects that the main reason is due to a decrease in exports. Although it also seems this is a result of higher imports, also leading to a lower growth in exports relative to imports, the impact on imports is not statistically significant. Household debt clearly holds a negative impact towards next exports, as well as growth in exports relative to imports. Not only does it lead to lower exports, but also higher imports. Non-financial firm debt contrasts with household debt, with an improvement of net exports and positive growth of exports relative to imports. Not only it increases exports, but also decreases imports. Both equality tests are statistically significant, for all cases (with the exception of the borrowing sector, when we isolate the exports in column 3). In columns 5 and 6, we isolate the share of consumption of imports and exports, respectively. However, none of the 4 debt/credit variables show statistical significance.

[11] Our conclusions are taken based on the change in net exports relative to initial GDP, $\frac{\Delta_3 NX_{it+3}}{Y_{it}}$, instead of the change in the net exports to GDP ratio in order to highlight the reversal of net exports. The pattern also holds using the change in the net export to GDP ratio.

Table 2.20: Credit Expansion, Net Exports, and Global Debt/Credit Cycle - Initial Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\frac{\Delta_3 NX_{it+3}}{Y_{it}}$	$\Delta_3 ln\frac{X_{it+3}}{M_{it+3}}$	$\frac{\Delta_3 X_{it+3}}{Y_{it}}$	$\frac{\Delta_3 M_{it+3}}{Y_{it}}$	$\Delta_3 s^{MC}_{it+3}$	$\Delta_3 s^{XC}_{it+3}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$
$\Delta_3 c^B_{it-1}$	0.0010	0.1038$^+$	-0.0680**	-0.0606*	0.0234	-0.0096	-0.1479**	-0.1642**	-0.1105**	-0.2365**
	(0.0174)	(0.05544)	(0.0229)	(0.0242)	(0.0245)	(0.0398)	(0.0288)	(0.0244)	(0.0207)	(0.0690)
$\Delta_3 c^{MBF}_{it-1}$	-0.0527**	-0.0678	-0.0962**	0.0178	-0.0042	0.0092	0.0235	-0.2920	0.0325	-0.0257
	(0.0187)	(0.0603)	(0.0249)	(0.0260)	(0.0263)	(0.0419)	(0.0225)	(0.6344)	(0.0227)	(0.0795)
$\Delta_3 c^H_{it-1}$	-0.0881**	-0.2562**	-0.0895**	0.1407**	0.0188	0.0129	-0.0701*	-0.1011**	-0.1416**	-0.1991*
	(0.0237)	(0.0752)	(0.0310)	(0.0329)	(0.0334)	(0.0524)	(0.0283)	(0.0340)	(0.0392)	(0.0954)
$\Delta_3 c^{NF}_{it-1}$	0.0728**	0.1577**	0.0794**	-0.0671**	0.0049	0.0057	-0.0256	0.0529*	-0.0186	0.9153
	(0.0167)	(0.0533)	(0.0220)	(0.0231)	(0.0234)	(0.0379)	(0.0190)	(0.0230)	(0.0192)	(1.0221)
$Global_{-i}\Delta_3 c^B_{it-1}$							-1.0654**			
							(0.1751)			
$Global_{-i}\Delta_3 c^{MBF}_{it-1}$								0.1021		
								(0.2137)		
$Global_{-i}\Delta_3 c^H_{it-1}$									-0.9736**	
									(0.2865)	
$Global_{-i}\Delta_3 c^{NF}_{it-1}$										-0.2022
										(0.2268)
Country Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Distributed Lags in Δy	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Test for equality (p-value):										
β_B and β_{MBF}	0.0022	0.0067	0.2796	0.0056	0.3344	0.6821				
β_H and β_{NF}	0.0000	0.0000	0.0000	0.0000	0.7497	0.9177				
R^2	0.1180	0.1516	0.5688	0.6244	0.0168	0.0237	0.4496	0.4369	0.1110	0.1108
Observations	1,018	1,018	1,018	1,024	1,024	1,018	1,035	1,035	1,035	1,035

Notes: This table reports regressions on the external sector, from t to t+3, on each of our 4 credit/debt to GDP variables, from t-4 to t-1. The dependent variable in column 1 is the change in net exports from t to t+3 relative to GDP in year t. Column 2 uses the change in log exports minus log imports over the same period as the dependent variable. Columns 3 and 4 show results for the change in exports and imports relative to initial GDP. The dependent variables in columns 5 and 6 are the change in the share of consumption imports in total imports, and the change in the share of consumption exports in total exports, respectively. Column 7-10 includes the global average change in each credit/debt to GDP variables over t-4 to t-1, excluding country i, in our main specification. All regressions include country fixed effects. Reported R^2 values are from within-country variation. Standard errors in parentheses are clustered at the country level. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

For a more detailed analysis on the impact on the external sector, we provide additional results in Table 2.21. In each of these cases, we include an additional interaction element with the credit/debt variables, called "openness". This additional element is calculated as the sample period average of total exports plus imports, scaled by GDP for a given country. We begin by repeating the analysis of the isolated credit/debt variables, to compare how they fare with the results in Table 2.20. The main difference seems to be for the bank credit, which has a negative impact on net exports relative to initial GDP. This is consistent and statistically significant for all the different scenarios. This would clarify the ambiguous effect we found before. The remaining effects are consistent with our previous results, and remain statistically significant, after adding the additional regressor, as well as with period fixed effects.

Without period fixed effects, the additional regressor has a positive and statistically significant impact on net exports relative to initial GDP, for all credit/debt variables. Not only that, their magnitude is much higher than the isolated coefficients. This yields an important conclusion: the overall effect of each credit/debt variable on net exports will depend on how open the economy is to the external sector. In our first three credit/debt variables, if the economy/country is too concentrated on the internal market, it will lead each of them to have a negative impact on net exports. But for countries/economies open enough to the rest of the world, it leads to a positive net effect on net exports. For the remaining variable, which is non-financial firm debt, the effect on net exports is always positive, where the degree of openness can further intensify the increasing effects on net exports.

With period fixed effects, the additional coefficients are only statistically significant for the household debt and the bank credit. Thus, it would seem that neither the market based finance (MBF) nor the non-financial firm debt effect on net exports would depend on the overall interaction of the country/economy with the rest of the world. Focusing on bank credit and household debt, recall that both have a negative impact on the economy in subsequent periods, both in terms of the GDP growth and unemployment. A positive effect on net exports and, thus, on GDP growth, could be helpful in either countering or minimizing the negative influence of a significant rise in either bank credit or household debt to GDP ratio. But this positive effect on net exports depends on how much the country/economy is open in terms of their reliance on external trade. The more open the country/economy is, the greater the positive effects on net exports, and the higher counterbalance to the negative impacts of household debt and bank credit have on GDP growth and unemployment.

Table 2.21: Credit Expansion, Net Exports, and Global Debt/Credit Cycle - Openness to International Trade

	(1) $\frac{\Delta_3 NX_{it+3}}{Y_{it}}$	(2) $\frac{\Delta_3 NX_{it+3}}{Y_{it}}$	(3) $\frac{\Delta_3 NX_{it+3}}{Y_{it}}$	(4) $\frac{\Delta_3 NX_{it+3}}{Y_{it}}$	(5) $\frac{\Delta_3 NX_{it+3}}{Y_{it}}$	(6) $\frac{\Delta_3 NX_{it+3}}{Y_{it}}$	(7) $\frac{\Delta_3 NX_{it+3}}{Y_{it}}$	(8) $\frac{\Delta_3 NX_{it+3}}{Y_{it}}$
$\Delta_3 c^{B}_{it-1}$	-0.0907**	-0.0947**	-0.1337**	-0.1113**	-0.0913**	-0.0763**	0.0066	-0.0792**
	(0.0328)	(0.0314)	(0.0322)	(0.0317)	(0.0348)	(0.0167)	(0.0187)	(0.0169)
$\Delta_3 c^{MBF}_{it-1}$	-0.0552**	-0.0563	0.0122	-0.0577**	-0.0569**	-0.0323	-0.0549**	-0.0338^{+}
	(0.0186)	(0.0487)	(0.0335)	(0.0192)	(0.0263)	(0.0271)	(0.0202)	(0.0196)
$\Delta_3 c^{H}_{it-1}$	-0.0950**	-0.0767^{+}	-0.2823**	-0.0875**	-0.1021**	-0.0535*	-0.2203**	-0.0527*
	(0.0237)	(0.0413)	(0.0602)	(0.0237)	(0.0251)	(0.0158)	(0.0476)	(0.0225)
$\Delta_3 c^{NF}_{it-1}$	0.0759**	0.0301	0.0553^{+}	0.0494^{+}	0.0732**	0.0181	0.0718**	0.0069
	(0.0166)	(0.0298)	(0.0302)	(0.0266)	(0.0178)	(0.0158)	(0.0178)	(0.0191)
$\Delta_3 c^{B}_{it-1} \times openness_i$	0.1597**				0.1634**			
	(0.0443)				(0.0456)			
$\Delta_3 c^{MBF}_{it-1} \times openness_i$		0.1319**				0.0084		
		(0.0465)				(0.0274)		
$\Delta_3 c^{H}_{it-1} \times openness_i$			0.4049**				0.2109**	
			(0.0870)				(0.0683)	
$\Delta_3 c^{NF}_{it-1} \times openness_i$				0.1472**				0.0272
				(0.0472)				(0.0264)
Country Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Distributed Lags in Δy	✓	✓	✓	✓	✓	✓	✓	✓
Period Fixed Effects					✓	✓	✓	✓
R^2	0.1297	0.1180	0.1280	0.1192	0.1685	0.1568	0.1655	0.1580
Observations	1,018	1,018	1,018	1,018	1,018	1,018	1,018	1,018

Notes: This table reports regressions on the net exports, from t to t+3, relative to GDP in year t, on each of our 4 credit/debt to GDP variables, from t-4 to t-1. We interact the change in each credit/debt variable with a country's openness to international trade, $openness_i$, defined as the average imports plus exports to GDP ratio during the sample period. All regressions include country fixed effects, and those in columns 5-8 also include period fixed effects. Reported R^2 values are from within-country variation. Standard errors in parentheses are clustered at the country level. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

When we isolate the lending sector, the bank credit coefficient on the share of consumption on imports becomes statistically significant, as well as the impact of market based finance (MBF) on imports. When we isolate the borrowing sector, the household debt becomes statistically significant for the share of consumption in total imports.

2.9.2 Predicting Global Growth

As we concluded in our previous subsection, economies/countries can lean on net exports to counteract or minimize the negative impacts that a rise on household debt or bank credit can have on economic growth or unemployment. But does this effect hold if/when all economies/countries are being affected by the negative effects of large bank credit or household debt at the same time? To address this issue, we begin by estimating the correlation between each country's credit/debt variables with their global levels:

$$\rho_i^{Global,n} = corr(\Delta_3 c_{it}^n, \frac{1}{N-1} \sum_{j \neq i} \Delta_3 c_{jt}^n) \tag{2.5}$$

Where n = {B, MBF, H, NF}. The correlation reflects by how much the debt/credit in each country i is correlated with the global debt/credit levels, where the latter variable is constructed excluding country i.

If we look at the evidence provided in Table 2.22, in columns 1-4, for the individual regressors, our previous results maintain, mainly for the impact of bank credit and household debt on future economic growth. For the interaction terms, we can see that, for 3 out of 4 of our credit/debt variables, countries/economies in which their credit/debt cycles present a higher correlation with the global credit/debt cycles reflect a steeper negative impact on subsequent GDP growth. This implies that, if other countries are also experiencing high levels of each of these credit/debt variables, the negative impact on country's i due to an expansion of these credit/debt variables on future GDP growth will be higher. Nevertheless, only the bank credit interaction term is statistically significant. For the remaining element, the non-financial firm debt, it seems to yield the opposite impact. If other countries/economies are experiencing higher debt/credit levels of non-financial firm debt, this is likely to amplify the positive effects of country i's increase of non-financial firm debt on GDP growth (this effect is statistically significant).

Table 2.22: Credit Expansion, Net Exports, and Global Debt/Credit Cycle - Correlation with Global Cycle

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+3}$	$\frac{\Delta_3 NX_{it+3}}{Y_{it}}$	$\frac{\Delta_3 NX_{it+3}}{Y_{it}}$	$\frac{\Delta_3 NX_{it+3}}{Y_{it}}$	$\frac{\Delta_3 NX_{it+3}}{Y_{it}}$
$\Delta_3 c^{B}_{it-1}$	-0.1131**	-0.1178**	-0.1738**	-0.2469**	-0.1203**	-0.0577**	-0.0676*	-0.0757**
	(0.0391)	(0.0205)	(0.0262)	(0.0689)	(0.0249)	(0.0155)	(0.0329)	(0.0167)
$\Delta_3 c^{MBF}_{it-1}$	0.0338	0.0545^{+}	0.0353	-0.0619	-0.0115	-0.0561*	0.0541	-0.0227
	(0.0263)	(0.0316)	(0.0264)	(0.0798)	(0.0169)	(0.0280)	(0.0331)	(0.0195)
$\Delta_3 c^{H}_{it-1}$	-0.0916**	-0.1095**	-0.0778^{+}	-0.1847^{+}	-0.0490*	-0.0368^{+}	0.0363	-0.0544*
	(0.0338)	(0.0277)	(0.0461)	(0.0951)	(0.0211)	(0.0208)	(0.0569)	(0.0226)
$\Delta_3 c^{NF}_{it-1}$	0.0178	-0.0078	0.0216	-0.1240	0.0166	0.0096	0.0138	0.0235
	(0.0236)	(0.0188)	(0.0237)	(0.0810)	(0.0148)	(0.0146)	(0.0303)	(0.0194)
$\Delta_3 c^{B}_{it-1} \times \rho_i^{Global,B}$	-0.1432*				0.1224**			
	(0.0642)				(0.0403)			
$\Delta_3 c^{MBF}_{it-1} \times \rho_i^{Global,MBF}$		-0.1147				0.0804*		
		(0.0523)				(0.0398)		
$\Delta_3 c^{H}_{it-1} \times \rho_i^{Global,H}$			-0.0568				-0.2404**	
			(0.0690)				(0.0830)	
$\Delta_3 c^{NF}_{it-1} \times \rho_i^{Global,NF}$				0.3995**				-0.0175
				(0.1483)				(0.0349)
Country Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Distributed Lags in Δy	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.1156	0.1100	0.1112	0.1217	0.1195	0.1311	0.1185	0.1193
Observations	1,035	1,035	1,035	1,035	1,018	1,018	1,018	1,018

Notes: This table reports regressions on the three year ahead economic growth, for columns 1-4, as well as in net exports, from t to t+3, relative to GDP in year t, for columns 5-8, on each of our 4 credit/debt to GDP variables, from t-4 to t-1. We interact the change in each credit/debt variable with $\rho_i^{Global,n}$, the correlation between country i's three-year credit/debt expansion and the sample average credit/debt expansion excluding country i given by equation (2.5). All regressions include country fixed effects. Reported R^2 values are from within-country variation. Standard errors in parentheses are clustered at the country level. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

In columns 5-8, we assess the influence on net exports instead. Again, the impact from the individual coefficients confirms our previous results. And as for the additional element, it seems that the lending sector has a positive impact, while the borrowing sector has as a negative impact. Only the non-financial debt coefficient is not statistically significant. For household debt, the negative impact on net exports when other countries/economies are also experiencing an increase in household debt is aggravated. This is possibly related to the negative effect that those countries also experience with an expansion in household debt, leading to them having less resources, and importing less goods as a result, which hurts exports in country i. This can also explain part of the negative impact of household debt on GDP is driven by its negative effect on net exports. Thus, the higher the correlation between the household debt cycles between different countries, the worse the impact on net exports and future economic growth. For the lending sector, we seem to have the opposite scenario. Even though higher bank credit or market based finance (MBF) have a negative impact on net exports, if other economies/countries in general boost their lending (independent of the segment), it yields positive outcomes for the net exports in country i. And the higher the correlation between the lending cycles, the higher the beneficial impacts on net exports. We could interpret that this effect is opposite of the household debt: increasing lending in other countries pushes for more resources in their economy, also pushing for more imports, which boosts exports in country i.

Both of these previous results open the path to evaluate the following possibility:

$$\Delta_3 y_{it+3} = \alpha_i + \beta_H \Delta_3 c^{H}_{it-1} + \beta_{NF} \Delta_3 c^{NF}_{it-1} + \beta_B \Delta_3 c^{B}_{it-1} + \beta_{MBF} \Delta_3 c^{MBF}_{it-1} + \beta_G Global_{-i} \Delta_3 c^{n}_{it-1} + \varepsilon_{it} \tag{2.6}$$

Where n = {B, MBF, H, NF}. The last term corresponds to the global three-year change in each of the credit/debt variable to GDP ratio, excluding country/economy i. These estimations do not include period fixed effects, as we are interpreting the global change in each credit/debt variable to GDP ratio as the time series variable that matters most for GDP growth in a given country i. In other words, we are putting an economic interpretation on the year fixed effects.

The results are presented in our previous Table 2.20, in columns 7-10. As before, the individual coefficients continue to confirm our previous results, with bank credit and household debt exerting a negative impact on subsequent GDP growth, and statistically significant, while non-financial firm debt and market based finance (MBF) exert a positive influence, but not statistically significant. As we can observe, for the additional regressor, the effect is negative for 3 out of the 4 credit/debt variables (the only one that is positive is the market based finance(MBF)), but it is only statistically significant for the bank credit and household debt. Not only that, the magnitude of each of these coefficients is very significant, pointing to the large relevance of this additional term for explaining movements in future economic growth. Since both the previous and additional variables are relevant for the bank credit and household debt, this would point to both the global cycle and country-specific cycle affecting the growth in country i. The magnitude of the coefficient also explains why we did not include period fixed effects, as it would under-estimate the relevance of this additional variable. Adding period fixed effects would reduce, or remove part of the variation in the global cycles, which is important to explain the GDP growth in specific countries/economies.

The estimations of the global credit/debt changes push to the following global time series regression:

$$\Delta_3 y_{t+3} = \alpha + \beta * \Delta_3 c^{H}_{t-1} + \gamma * \Delta_3 c^{NF}_{t-1} + \theta * \Delta_3 c^{B}_{t-1} + \omega * \Delta_3 c^{MBF}_{t-1} + \varepsilon_t \tag{2.7}$$

Notice that the difference between this last specification and the previous estimations is the removal of the "i" term, that is, instead of estimating for each country, we calculate the average across different countries in our sample, for each of the variables, for each year, resulting in a single time series estimation.

When we look at Table 2.23, columns 1 to 4 reflect a strong global cycle, mainly for the lending sector. A rise in the global bank lending cycle from 4 years ago to the previous year predicts a lower GDP for the next three years. For the market based finance (MBF), we have the opposite effect, although the magnitude of the coefficient is lower. For the borrowing sector, the household debt is also significant, but the impact on GDP is small, while the non-financial firm debt is not significant. The remaining columns show the robustness of our findings, when we estimate with all the 4 credit/debt variables (column 5), when we control for distributed lags of the dependent variable (column 6), and when we just consider the period before the Great Financial Crisis (column 7). In fact, in those cases, non-financial debt becomes statistically significant. When we isolated either the borrowing or the lending sector, the results were similar. The main difference was a higher magnitude for the household debt coefficient.

Table 2.23: Global Debt/Credit and Global Growth

	Dependent variable: global average $\Delta_3 y_{t+3}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Global $\Delta_3 c^{B}_{t-1}$	-0.7562**				-0.2678**	-0.6081**	-0.9706**
	(0.0681)				(0.0228)	(0.0222)	(0.0243)
Global $\Delta_3 c^{MBF}_{t-1}$		0.1209**			-0.1647**	0.2502**	0.7373**
		(0.0073)			(0.0185)	(0.0268)	(0.0296)
Global $\Delta_3 c^{H}_{t-1}$			-0.0246*		-0.7771**	-0.0170	-0.0880**
			(0.0122)		(0.1174)	(0.0225)	(0.0251)
Global $\Delta_3 c^{NF}_{t-1}$				0.0233	0.6305**	0.2449**	0.2566**
				(0.0155)	(0.0511)	(0.0115)	(0.0103)
Global Δy_{t-1}						0.6812**	0.7381**
						(0.0278)	(0.0285)
Global Δy_{t-2}						0.3315**	0.3640**
						(0.0299)	(0.0320)
Global Δy_{t-3}						0.0984**	0.0863**
						(0.0243)	(0.0245)
Sample	Full	Full	Full	Full	Full	Full	Pre2006
Test for equality (p-value):							
β_B and β_{MBF}					0.0024	0.0000	0.0000
β_H and β_{NF}					0.0000	0.0000	0.0000
R^2	0.0013	0.0162	0.0017	0.0349	0.0514	0.0830	0.3057
Observations	59	59	59	59	59	59	44

Notes: This table reports the time series regressions of the average across the different countries in our sample, for real GDP growth between t and t+3, on the change in credit/debt variables to GDP ratio from t-4 to t-1. Newey-West standard errors in parentheses are computed with 6 lags. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

The previous results are based on time series data alone, as we mentioned before, and thus require some care in terms of interpretation. In terms of the time series component of our data, recall that we consider a total number of 61 years (subjected to available data for each variable). Our concern is that there may be additional factors unrelated to our credit/debt variables that explain the results in Table 2.23.

We take into account additional possibilities in Table 2.24. For columns 1-4, we introduce linear and quadratic trends, and consider the differences between the impacts for the full sample, and the sample just until 2006. In general, the coefficients for our 4 credit/debt variables are similar. The main difference is for the bank credit, in column 4. There is a significant decrease of the magnitude of the coefficient, and a significant increase of the magnitude of the household debt coefficient. As for the additional trend term, it seems to be significant in all scenarios, where the linear term has a negative impact, and the quadratic term has a positive influence. The combination of these effects would imply that the trend has a negative impact on subsequent GDP growth, but that impact is smaller the higher the value of the trend. In columns 5 and 6, we construct the aggregate levels for the global variables across countries, instead of the unweighted averages, both for the credit/debt and the output variables. The variables are still statistically significant, for both the full sample, and just the sample before 2006. Again, the main difference seems to be a lower impact for the bank credit coefficient. When we isolate the lending sector, the results are fairly similar. The main differences is a higher magnitude in the coefficients in column 4, and in column 5, a lower magnitude for the bank credit coefficient, and a higher magnitude for the market based finance(MBF) coefficient. When we isolate the borrowing sector, the results were fairly similar.

Table 2.24: Global Debt/Credit and Global Growth: Robustness

	Dependent variable: global average $\Delta_3 y_{t+3}$				Dependent variable: global aggregate $\Delta_3 y_{t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Global $\Delta_3 c^{B}_{t-1}$	-0.6740**	-0.8872**	-0.6458**	-0.0936**		
	(0.0209)	(0.1404)	(0.0231)	(0.0200)		
Global $\Delta_3 c^{MBF}_{t-1}$	0.5182**	0.2345**	0.4769**	0.2989**		
	(0.0269)	(0.0189)	(0.0306)	(0.0210)		
Global $\Delta_3 c^{H}_{t-1}$	-0.1378**	-0.1637**	-0.1372*	-0.4254**		
	(0.0255)	(0.0183)	(0.0620)	(0.0197)		
Global $\Delta_3 c^{NF}_{t-1}$	0.1315**	0.2442**	0.1222**	0.0802**		
	(0.0113)	(0.0650)	(0.0118)	(0.0078)		
Global agg. $\Delta_3 c^{B}_{t-1}$					-0.1846**	-0.1604**
					(0.0659)	(0.0696)
Global agg. $\Delta_3 c^{MBF}_{t-1}$					0.2804**	0.3083**
					(0.0945)	(0.0101)
Global agg. $\Delta_3 c^{H}_{t-1}$					-0.5815**	-0.1026**
					(0.1167)	(0.0126)
Global agg. $\Delta_3 c^{NF}_{t-1}$					0.1945**	0.2123**
					(0.1046)	(0.1161)
Trend	-0.1065**	-0.1800**	-0.3631**	-0.6000**		
	(0.0033)	(0.0257)	(0.1251)	(0.1304)		
Trend^2			0.0885**	0.0263**		
			(0.0314)	(0.0003)		
Sample	Full	Pre2006	Full	Pre2006	Full	Pre2006
Distributed lag in Δ_y	✓	✓	✓	✓	✓	✓
Test for equality (p-value):						
β_B and β_{MBF}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
β_H and β_{NF}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.1808	0.1219	0.1948	0.3393	0.2710	0.2904
Observations	59	44	59	44	59	44

Notes: This table reports several robustness tests for the global time series regressions in Table 2.23. Columns 1-4 control for a linear or a quadratic trend in the specification in Table 2.23 for the full and pre-2006 samples. Columns 5-6 compute the aggregate global variables by summing the dollar levels of all variables and then computing each variable based on the summed global aggregate. Each column includes three lags in the global one-year change in log GDP, computed using the relevant aggregation method. Newey-West standard errors in parentheses are computed with 6 lags. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

2.10 Conclusion

We seek to evaluate the impact of the different segments within the lending sector to the private non-financial sector can have on subsequent GDP growth. We isolate the bank lending channel as one of the main components, and group the remaining ones into a second segment which we classify as market based finance (MBF). We also include the 2 different segments of the borrowing sector, household debt and non-financial firm debt, to compare with the results obtained by [Mian et al., 2017a]. We debate the main source of these effects, and focus on either credit demand or credit supply shocks, in addition to other alternatives.

Our sample consists of a country-level unbalanced panel dataset, with 136 different countries, between 1960 and 2021, with an annual frequency. We focus on the impact that a 3 year change in each of the 4 credit/debt variables (between t-4 and t-1) can have on a 3-year change in subsequent GDP growth (between t and t+3). As for the source of these effects, we consider 6 different instrumental variables: the real sovereign spread (spr^{real}), the mortgage sovereign spread (spr^{MS}), the corporate credit spreads (spr^{corp}), the Excess Bond Premium (EBP), the Financial Conditions Index (FCI), and the Principal Component (PCA), which is a combination of all 5 previous instruments. In terms of robustness to our results, we provide different alternative scenarios, with interactions with the public sector and government accounts, with the external sector, different sets of country and period fixed effects, subsamples, forecasts, and others.

We find that a rise in bank credit and/or household debt to GDP ratio lowers subsequent GDP growth. The predictive power is large in magnitude and robust across time and space. The bank credit booms and household debt booms are connected to lower interest rate spread environments, as well as periods with better financial conditions. And although the overall impact on subsequent GDP growth is negative, we found contrasting evidence when using the Financial Conditions Index (FCI) as an instrument. This would point to the potential different effects that bank credit and household debt could have on future economic growth (good booms vs bad booms), depending on the underlying cause of the boom. Nevertheless, it is clear that most of them would lead to a negative effect on the economy. We also find significant evidence of low interest rate spreads and better financial conditions leading to booms for market based finance (MBF) and non-financial firm debt. Their impact on subsequent GDP growth, on the other hand, is more dubious. In general, it yields positive effects, but it does not retain statistical significance in all the different scenarios.

We consider the role of biased or rational expectations, and show that professional forecasters systematically overstate output growth towards the end of the bank credit boom. When it comes to macroeconomic frictions, they are relevant for both household debt and bank credit. Their effect is non-linear on future economic growth: an expansion in credit/debt leads to a decrease of future economic growth, but a fall in debt/credit does not increase subsequent GDP growth. For bank credit, the negative effect is reinforced with constraints on monetary policy. A rise in either household debt or bank credit also leads to higher levels of unemployment. We also uncover evidence of global credit/debt cycles. Countries with a household debt cycle or bank credit cycle more correlated with the global cycle (with the corresponding cycles in other countries), experience a more robust decline in GDP growth in response to an expansion in household debt or bank credit.

The results and the evidence that we found are more consistent with models where the fundamental source of the changes in household debt or bank credit lie in changes in the credit supply (credit supply shocks), rather than credit demand or other possibilities. This would likely be connected to incorrect expectations formation by lenders and investors (what many authors classify as “credit market sentiment” in the literature), which is an important element in explaining shifts in credit supply. Although credit demand shocks could play an important role in prolonging or amplifying the effects of the booms, it is unlikely that they are the source, as it would lead to results that conflict with empirical evidence.

We could interpret that the reason we find that both bank lending and household debt are statistically significant, and that both have a negative impact on subsequent GDP growth, is due to their connection (that is, most bank lending would be contracted by the household borrowing sector). Although we do not have the specific allocations between each of the 2 subsectors of lending and borrowing, one would expect that households are more likely to resort to bank lending than to market based finance (MBF), when compared to non-financial firms. However, not all the results are consistent with this connection. When we decompose consumption between durables, non-durables and services, we can see that bank credit has a positive impact on the consumption of services and non-durables. And even though the impact on durables is negative, it is not statistically significant. This could be interpreted as a lack of a connection between the household debt and bank credit. Given that the main destination of household debt is mortgage credit, which would fall under the category of durable goods, and one would expect most households resorting to bank credit instead of market based finance, one would expect the coefficient for consumption of durables associated with bank credit to be positive, which is not the case. Another difference would be in terms of the correlation with the global cycles. While the correlation between the bank credit cycle in a specific country/economy and the global bank credit cycle has a positive effect on net exports, the opposite is true for the household debt. Finally, we find some differences in terms of statistical significance and magnitude in the different scenarios, where the bank credit shows more robustness to different specifications than the household debt. This would imply that there is a significance of the bank credit that goes well beyond the household debt. It would also mean that the main component that generates the boom bust cycle in GDP would be the bank credit, independent of its destination, rather than household debt, independent of its financing. Thus, some caution would be advised on assuming such a connection.

Additional caution should also be taken with regard to our results. For example, our sample period, which starts since 1960, a period that, according to [Jorda et al., 2015], has witnessed "an unprecedented surge in the scale and scope of financial activities in advanced economies". The relevance of the bank credit segment and the household debt segment could be reflecting increases in financialization of the economy. There are several institutional factors that cause differences across countries in their financial dependence and level of economic development. Our results do not necessarily take this component directly into account, and do not directly relate to the literature on cross-country differences in financial development and economic growth.

When we compare our results with the recent work of [Barauskaitė et al., 2022], they seem to find that both bank lending and market based finance (MBF) lending channels are statistically significant, which contrasts with our results, where the bank lending is the more statistically significant channel. When we restrict our sample to match the same countries in their sample, however, the statistical significance of the market based finance (MBF) channel increases, although the bank lending remains the most significant. Thus, we can conclude that a possible explanation would be the consideration of the whole private non-financial borrowing sector (household debt + non-financial firm debt), whereas this paper only considers the non-financial firm sector for borrowing. Since households are more likely to resort to bank lending than to market based finance (MBF), when compared to non-financial firms, the significance of market based finance (MBF) is likely to increase when we restrict the sample to non-financial firms. Nevertheless, this component remains to be thoroughly tested in future work.

Another avenue for future expansions would be to evaluate the heterogeneity, either in terms of borrowing or lending channels. As we discussed, the relevance of the lending channels tends to change according to the countries considered. It would be relevant to try to classify different countries or regions according to the relevance of each sector, and also attempt to explain why. For example, this could reflect different characteristics in the financial systems in each region. Or could be the different destinations (in terms of borrowing) that are given to the credit lending that could explain the difference in the relevance of each channel.

We could also consider to evaluate the general government sector, to infer if there is a higher exposure of the public sector to one of the lending channels. As we found in Table 2.2, public debt seems to have a significant negative impact on future GDP growth.

2.11 Appendix

2.11.1 Data Appendix

Here, we provide a detailed list of variables that we use in the model, and the source of the data:

1. *Household debt and non-financial firm debt*: Household and non-financial firm debt are from the BIS's "Long series on credit to the private non-financial sector" database[12]. This constitutes the whole private non-financial borrowing sector. The entire non-financial sector would also include the general government, which we do not consider here.

2. *Bank credit and market based finance (MBF) credit*: These are also obtained from the "Long series on credit to the private non-financial sector" database, and correspond to the lending sector of the private non-financial sector. There are 2 classifications for the lending sector: "bank" and "total". As a result, we retrieve the data from the "bank channel", and calculate the difference between the "total" lending and the "bank" lending, and classify this channel as the "market based finance (MBF)", which consists of all the lending granted outside of the banking sector.

3. *National Accounts*: We obtain the data for the National accounts data from the World Bank's World Development Indicators (WDI) database. We use annual frequency in current and constant prices on GDP, "Y", household consumption, "C", gross capital formation, "I", and government consumption, "G". We supplement this data on total household consumption with data on household consumption expenditure on durable goods, "C^{dur}", non-durable goods, "C^{nondur}", and on services, "$C^{services}$", from the OECD as well. Finally, we also gather data on investment by type of good from the OECD.

4. *Exports, imports, and the current account*. Data on exports, "X", imports, "M ", and current account, "CA", in current prices, are taken from both the from the International Monetary Fund's International Financial Statistics (IFS) database and the OECD, depending on data availability. When data is available for both, we prioritized the data from the IMF. However, the values for periods and countries that are available in both datasets were exceedingly similar. Net exports is the difference between exports and imports, "NX" = "X" - "M".

5. *Disaggregated exports and imports*. In addition to overall exports and imports, we construct variables for the share of consumption in total exports and imports, s^{XC} and s^{MC}, respectively. We start by taking the data from the NBER-UN World Trade database (from 1962-2000) and UN Comtrade (from 2000-2012). The different categories are identified

[12]Source: https://www.bis.org/statistics/totcredit/credpriv_doc.pdf

according to the SITC (Standard International Trade Classification) codes. We can connect to the destination of imports and exports using the BEC "Basic Economic Categories" classification, which groups the SITC codes into 3 main categories: consumption; capital; and intermediate. Therefore, we keep only the trade information with the destination for consumption. Finally, according to the "Basic Economic Categories" classification, some codes could fit into more than one category (for example, 51, or 321 could be included either in the intermediate or consumption category). As a result, we compared the data for the few years that we have for both data sources, when we included and when we excluded these codes. Since the values between the 2 sources matched closer when we excluded these codes, they were not classified as consumption imports or exports.

6. *Unemployment rate*. Data on unemployment rates, u, are obtained from the OECD harmonized unemployment rate database, as a starting point. For the remaining missing data, we complement using International Monetary Fund's International Financial Statistics (IFS) database first, and then use other OECD unemployment rate data (more specifically, we also use the long-term unemployment rate, and the unemployment rate forecast). The harmonized unemployment rate is measured by applying the same definition of unemployment across OECD member countries to obtain estimates that are more internationally comparable. However, since we focus on changes in the unemployment rate, level differences in definitions that are constant over time will not bias the results.

7. *Sovereign and credit spreads*. The sovereign spread, spr, is constructed as the difference between the 10-year government bond yield and the 10-year U.S. Treasury yield. In the original article, the Government 10-year bonds yields were obtained from the Global Financial Data. Given that this source was unavailable, we constructed this data from the combination of 2 sources: 1 - The Government 10-year bonds yields from the OECD, provided under the "Main Economic Indicators" section; 2 - for the remaining missing data, we add the Government 10-year bonds yields from Datastream (REFINITIV, Reuters). For the 10-year U.S. Treasury yield, we retrieve this data from FRED (Federal Reserve Economic Data). The real sovereign spread is the nominal spread minus the difference in CPI (Consumer Price Index) inflation rates. For the CPI, we use the data provided by the IMF's International Financial Statistics (IFS).

8. *Mortgage-sovereign spread*, spr_t^{MS}, is the difference between the mortgage lending rate and the 10-year government bond yield. The source of the second element was described in the previous point. For the mortgage lending rate, in the original article, the authors compile data from Global Financial Data and Datastream. In our case, since we are not able to access the Global Financial Data, we focus on the data provided by Datastream (REFINITIV, Reuters), more specifically, from the building society mortgages.

9. *Corporate credit spreads*, spr_t^{corp} , are constructed as the difference between the corporate bond yield and the 10-year government bond yield. Again, in the original article, this was taken from the Global Financial Data. In our case, we took the "interest rates to Non-Financial corporations" from the IMF's Monetary and Financial Statistics (MFS). For the United States the corporate credit spread is the Baa-Aaa spread (average of Q4 monthly values).

10. For all the interest rate series, all values were aggregated to annual series by taking quarterly averages of daily, weekly, or monthly rates and using the fourth quarter value. For Eurozone countries, we use the Germany 10-year government bond yield as the benchmark rate.

11. *EBP: Excess Bond Premium.* We obtain the data for the EBP for the US, at the Federal Reserve website (can also obtain from the Gilchrist database)[13] as well as for seven European countries (Austria, Belgium, Germany, France, United Kingdom, Italy, and the Netherlands), which is obtained from the dataset provided in the [Bleaney et al., 2016] paper.

12. *FCI: Financial Conditions Index*. We start by using the dataset provided by the IMF, in the Global Financial stability report, from October, 2017[14]. The data is provided for a total of 21 countries in our sample, between 1973 and 2016. The FCI from the IMF was calculated following the [Koop and Korobilis, 2014] methodology. For the more recent periods, we use the FCI provided by Bloomberg.

13. *Professional GDP growth forecasts and forecast errors*. We use GDP growth forecasts and forecast errors from the IMF World Economic Outlook (WEO) Historical Forecasts Database and from print editions of the OECD Economic Outlook. Forecasts from the OECD Economic Outlook are hand-collected. Forecast errors are defined as the difference between realized and forecasted growth. We calculate the forecast errors for the different horizons (1 year ahead, t+1, until 5 year ahead, t+5). The WEO Historical Database reports forecasts for growth up to the five-year horizon since 1990. We supplement this information with one-year and two-year ahead forecasts from the OECD Economic Outlook are available since 1970 until 1990, respectively.

14. *Government debt to GDP*. The government debt to GDP ratio, "GD/Y", is from the IMF's Historical Public Debt Database ([Abbas et al., 2010]), which contains information until 2015. We complemented the remaining information with the IMF gross debt (as % of GDP) between 2015 and 2021.

[13]Source:https://www.federalreserve.gov/econres/notes/feds-notes/updating-the-recession-risk-and-the-excess-bond-premium-20161006.htm

[14]Source: https://www.imf.org/en/Publications/GFSR/Issues/2017/09/27/global-financial-stability-report-october-2017

15. *Real house prices*. The data is based on the BIS's "Long series on nominal residential property prices". These series cover 41 countries in our sample. Annual growth in real house prices is constructed from changes in fourth quarter values, deflated by the CPI.

16. *Real effective exchange rates*. Real effective exchange rates, "REER", are from the BIS's "Effective exchange rate indices" database. We use the narrow indices, which contain data from 1964 until 2022, and are available for 24 of the countries in our sample. An increase in the index compared to the previous period implies an appreciation of the currency.

17. *Exchange rate regime*. Originally, the information on the exchange rate regime comes from [Reinhart and Rogoff, 2004], which was more recently updated in [Ilzetzki et al., 2019] [15], with data until 2019. We use the "coarse" classification codes, which range from 1 to 6. We define "Fixed regimes" as arrangements with a coarse classification code equal to 1 (currency boards, a pre-announced horizontal band that is narrower than or equal to $\pm 2\%$, or a de facto peg). "Intermediate regimes" are defined as arrangements with a classification code of 2 or 3 (crawling pegs, crawling bands, managed floating, moving bands, etc.). The remaining categories are classified as "Freely Floating", which would be the arrangements with a coarse classification code equal to 4 or 5. The classification of 6 is for missing data.

2.11.2 Additional Tables and Figures

[15] Source: https://www.ilzetzki.com/irr-data

Table 2.25: Summary of main countries in the sample and Key Statistics

Country	Average Δc^{H}	Average Δc^{NF}	Average Δc^{B}	Average Δc^{MBF}	Std. dev. Δc^{H}	Std. dev. Δc^{NF}	Std. dev. Δc^{B}	Std. dev. Δc^{MBF}
Argentina	0.03	0.01	0.20	0.29	0.77	11.37	14.69	27.60
Australia	2.55	1.36	2.06	0.40	4.48	5.43	2.58	2.69
Austria	1.62	3.25	1.43	0.96	6.16	9.46	2.70	1.28
Brazil	0.96	0.70	1.44	0.21	1.05	2.71	2.73	2.40
Canada	1.47	1.42	1.55	1.06	2.14	3.22	2.28	3.50
Chile	2.14	4.62	0.98	1.23	3.81	15.13	3.11	4.49
China	3.37	3.48	4.56	1.07	2.14	7.78	10.67	3.05
Colombia	1.08	1.04	1.56	0.58	2.52	6.08	4.73	8.66
Czech Republic	1.21	1.42	-0.17	0.06	1.68	11.52	3.43	2.33
Denmark	3.39	4.20	2.55	1.31	10.83	10.17	9.80	3.49
Finland	1.28	2.02	1.32	1.02	2.83	8.32	2.56	5.18
France	1.43	3.27	1.92	2.13	2.27	10.41	6.40	4.17
Germany	0.96	1.21	1.22	0.69	4.00	5.50	4.43	2.49
Greece	2.11	2.26	1.26	1.05	2.70	4.94	5.57	2.89
Hungary	0.39	1.30	0.59	1.10	2.37	4.58	4.58	2.69
India	0.31	0.96	0.70	0.40	3.01	6.10	1.32	1.54
Indonesia	0.80	1.02	0.38	0.01	1.26	3.39	6.28	5.07
Ireland	-0.99	4.62	-0.35	3.24	8.99	26.56	9.68	17.81
Israel	1.02	1.61	1.92	1.20	3.30	6.17	6.01	5.82
Italy	0.70	1.01	1.33	-0.49	1.47	5.97	6.97	6.98
Japan	1.09	1.63	0.81	1.05	2.49	10.11	2.84	13.24
Luxembourg	1.19	9.76	2.20	7.65	1.34	20.87	4.50	20.82
Malaysia	1.37	0.64	2.33	0.09	2.62	2.42	6.12	0.96
Mexico	0.52	0.59	0.39	0.43	1.79	6.17	2.88	3.48
Netherlands	2.91	3.91	1.39	2.16	7.40	16.52	2.76	3.71
New Zealand	2.94	0.58	2.31	0.40	4.44	5.18	3.90	2.42
Norway	1.52	1.50	1.24	2.52	3.07	5.88	4.12	10.02
Poland	1.28	1.53	0.96	0.76	1.67	3.57	2.33	1.70
Portugal	1.61	1.92	1.53	1.09	3.24	13.13	6.34	4.19
Russia	0.94	2.51	1.82	1.63	1.03	5.15	2.31	3.43
Saudi Arabia	0.33	1.71	1.70	0.40	1.35	5.39	4.70	1.98
South Africa	-0.57	-0.14	0.22	-0.04	0.84	1.64	2.12	0.92
South Korea	1.79	1.79	2.56	1.03	1.89	5.34	5.45	1.90
Spain	1.35	2.23	0.83	1.13	4.04	9.26	6.45	2.48
Sweden	2.03	4.09	1.15	1.71	5.74	8.18	3.67	3.77
Switzerland	4.83	5.50	2.59	1.47	16.07	13.96	7,90	3.92
Thailand	2.78	2.08	2.37	0.93	5.31	16.65	7.60	3.17
Turkey	0.45	1.49	1.33	0.62	1.12	3.39	3.16	1.74
United Kingdom	1.47	1.01	1.16	0.74	3.80	3.37	2.68	3.18
United States	0.65	0.76	0.26	1.16	1.99	1.74	1.66	2.02
Average	1.41	2.18	1.39	1.15	3.48	8.08	4.87	5.12

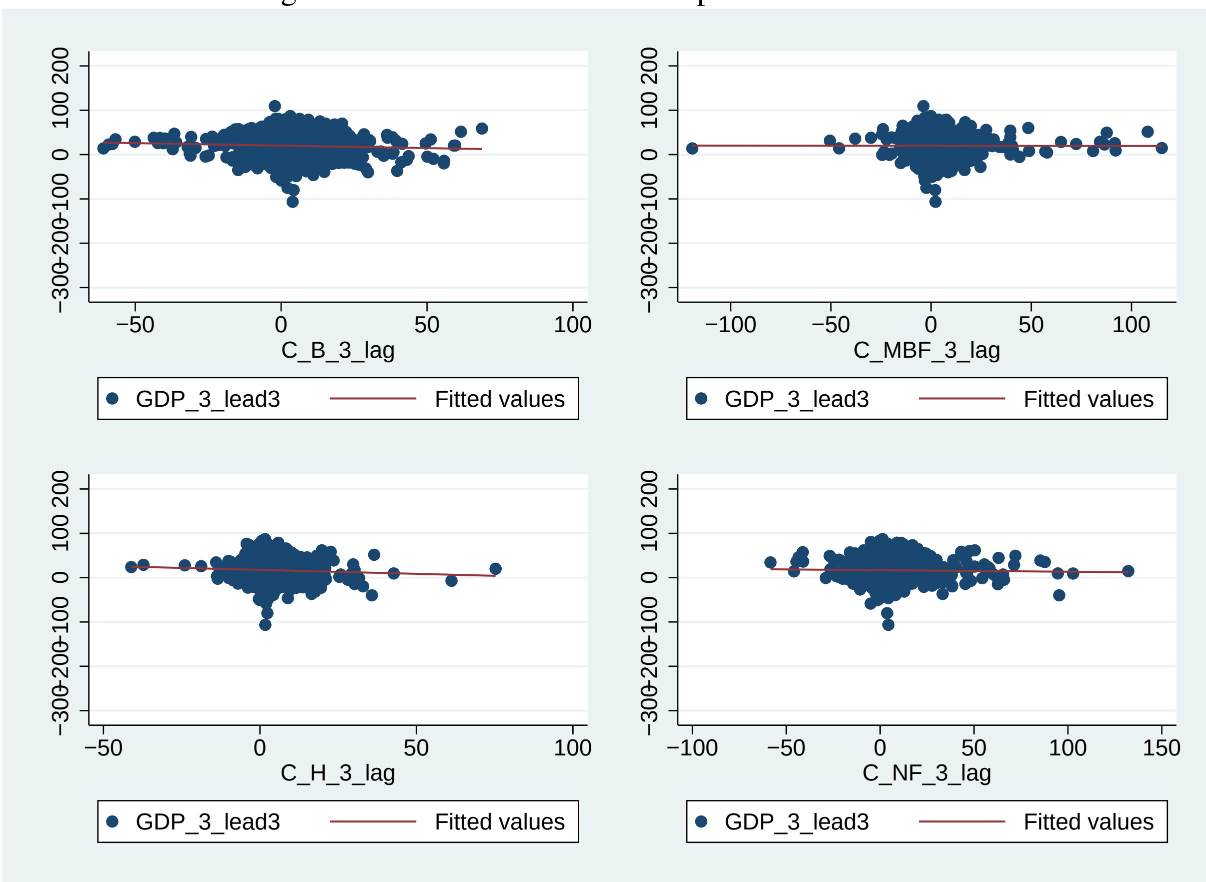
Notes: The table contains the list of the main countries in our sample (41 out of the 136), as well as the mean and the standard deviation of household debt, non-financial firm debt, bank credit and market based finance (MBF).

Table 2.26: Summary statistics

Variable	N	Mean	Median	SD	$\frac{SD}{SD(\Delta y)}$
Δy	6953	3.51	3.84	5.71	1
$\Delta_3 y$	6953	10.86	11.20	11.83	2.07
$\Delta c^{Private}$	1994	2.56	1.73	10.14	1.77
$\Delta_3 c^{Private}$	1994	6.80	5.45	16.45	2.88
Δc^{H}	1994	1.39	0.95	4.20	0.74
$\Delta_3 c^{H}$	1994	3.42	2.78	7.15	1.25
Δc^{NF}	1994	2.06	0.96	8.99	1.57
$\Delta_3 c^{NF}$	1994	4.64	3.10	14.41	2.52
Δc^{B}	1994	1.38	0.95	5.51	0.96
$\Delta_3 c^{B}$	1994	3.55	2.91	10.55	1.85
Δc^{MBF}	1994	1.09	0.55	6.79	1.19
$\Delta_3 c^{MBF}$	1994	3.10	1.81	10.68	1.87
$\Delta_3 d^{Gov}$	5964	1.90	1.85	20.04	3.51
$\Delta_3 d^{NetForeign}$	4917	-7.03	-7.73	24.04	4.21
Δc	6166	6.71	6.92	14.08	2.51
Δc^{dur}	1022	6.44	5.44	13.30	2.33
Δc^{nondur}	762	1.70	1.58	2.97	0.52
C/Y	6626	-0.01	-0.01	0.11	0.02
Δi	6953	4.08	4.50	14.34	2.51
Δg	6237	3.84	3.25	9.87	1.73
Δx	4437	7.84	7.94	22.35	3.91
Δm	4373	7.74	8.10	20.39	3.57
$\Delta NX/Y$	3999	-0.05	0.00	2.05	0.36
$\Delta CA/Y$	5060	-0.02	-0.02	4.27	0.75
Δs^{XC}	4141	0.14	0.01	18.38	3.22
Δs^{MC}	4074	0.17	0.03	4.17	0.73
$\Delta reer$	1311	-0.06	0.32	5.32	0.93
Δu	3197	0.03	-0.05	1.66	0.29
$\Delta_3 u$	3197	-0.05	-0.02	7.12	1.25
$\Delta_3 y_{t+3\|t}$	3818	-0.06	-0.05	1.78	0.31
$\Delta_3 (y_{t+3} - y_{t+3\|t})$	3818	-0.13	0.07	6.65	1.16
$\Delta_3 ln(P^{Housing})$	1316	12.63	7.70	31.03	5.43
spr^{real}	1841	1.87	0.83	4.21	0.74
spr^{MS}	832	1.08	1.21	2.13	0.37
spr^{corp}	370	0.57	0.89	1.90	0.33
EBP	100	-0.02	-0.11	0.54	0.10
FCI	704	3.31	2.91	2.16	0.38

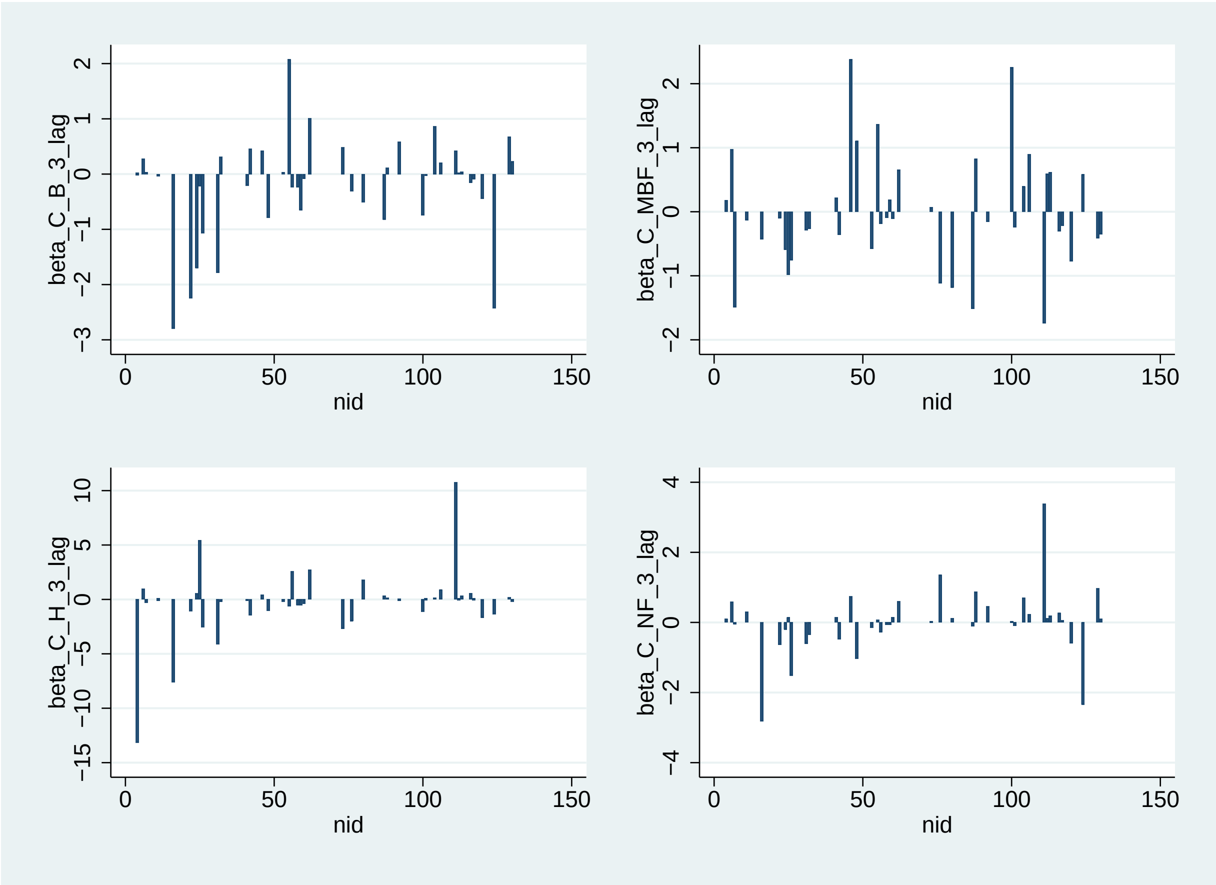
Notes: Log changes and ratios are multiplied by 100 to report changes in percentages or percentage points. Δ and Δ_3 denote to one-year and three-year changes, respectively. The variables description is provided in subsection 2.3.2.

Figure 2.2: Debt/Credit to GDP expansions and Growth



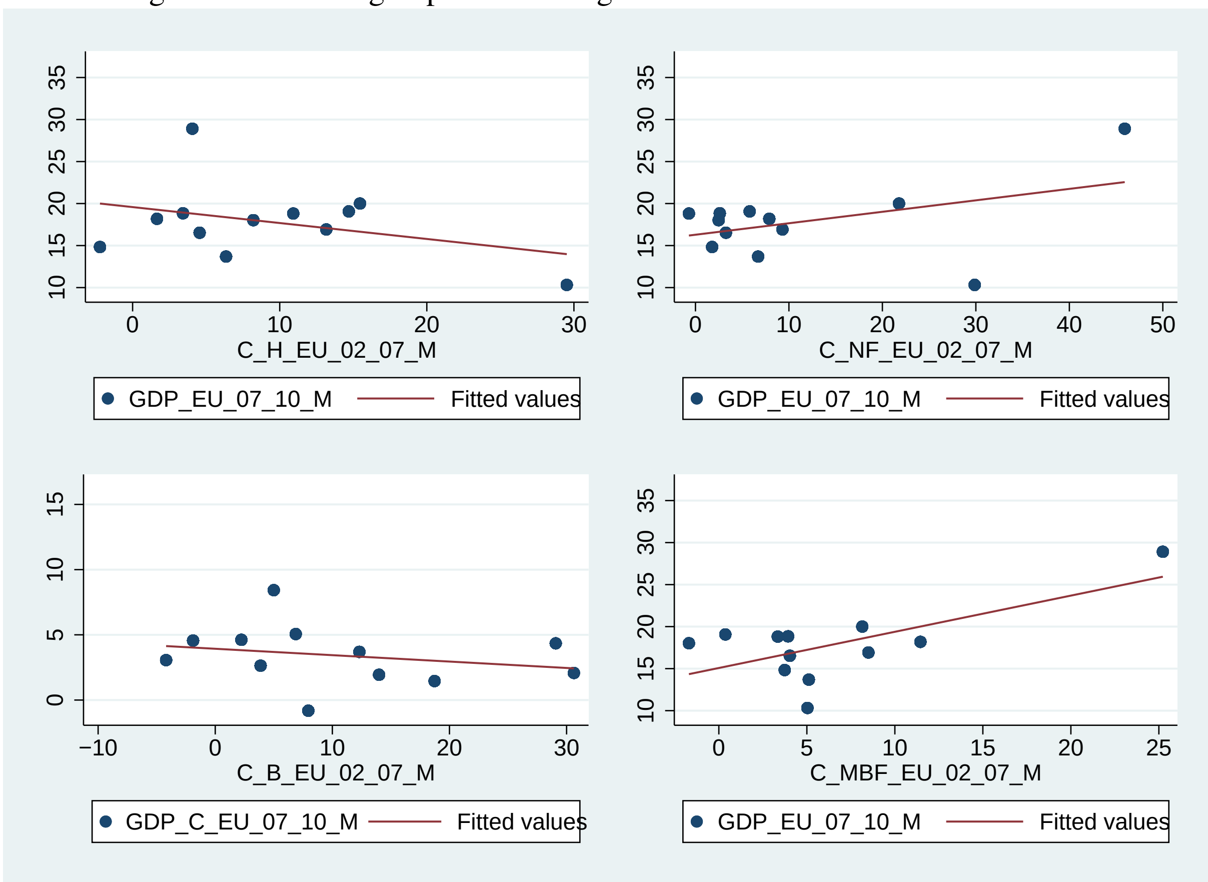
Notes: This figure plots the relationship between GDP growth from t to t+3 and the expansion in household and firm debt to GDP from t-4 to t-1, as well as the expansion in bank credit and market based finance (MBF) to GDP from t-4 to t-1. Each point refers to year t. The red line corresponds to the fitted values.

Figure 2.3: Beta coefficient estimations for each type of credit (β_B, β_{MBF}, β_H, and β_{NF}), for each country



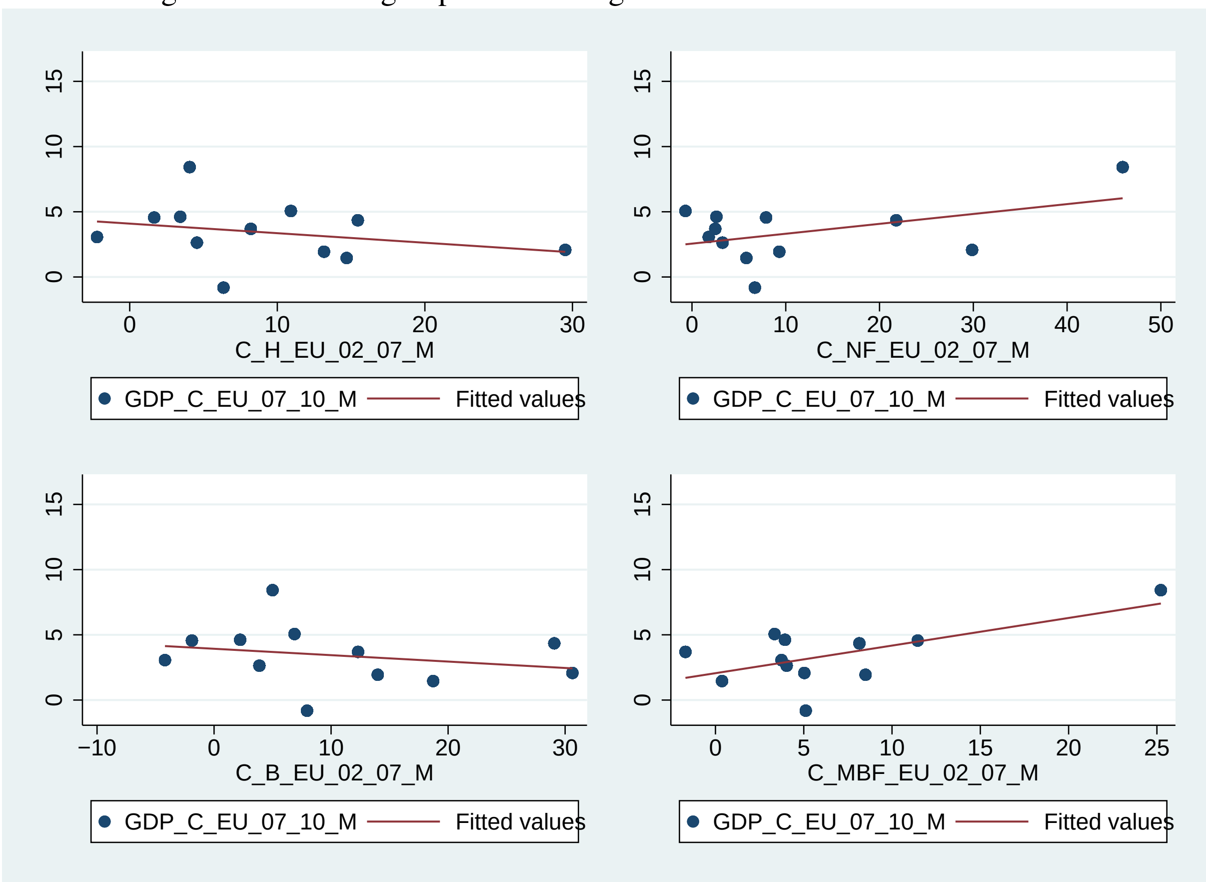
Notes: This figure plots β_B, β_{MBF}, β_H, and β_{NF} from the time series regression, $y_{it+3} - y_{it} = \beta_0 + \beta_{n,i}\Delta_3 c^n_{it-1} + \sum_{j=1}^{3} \gamma_j \Delta y_{it-j} + \varepsilon_{it}$, estimated separately for each country i in the sample, where $n = \{B, H, NF, MBF\}$.

Figure 2.4: Sovereign Spread Convergence in the Eurozone: OLS estimation



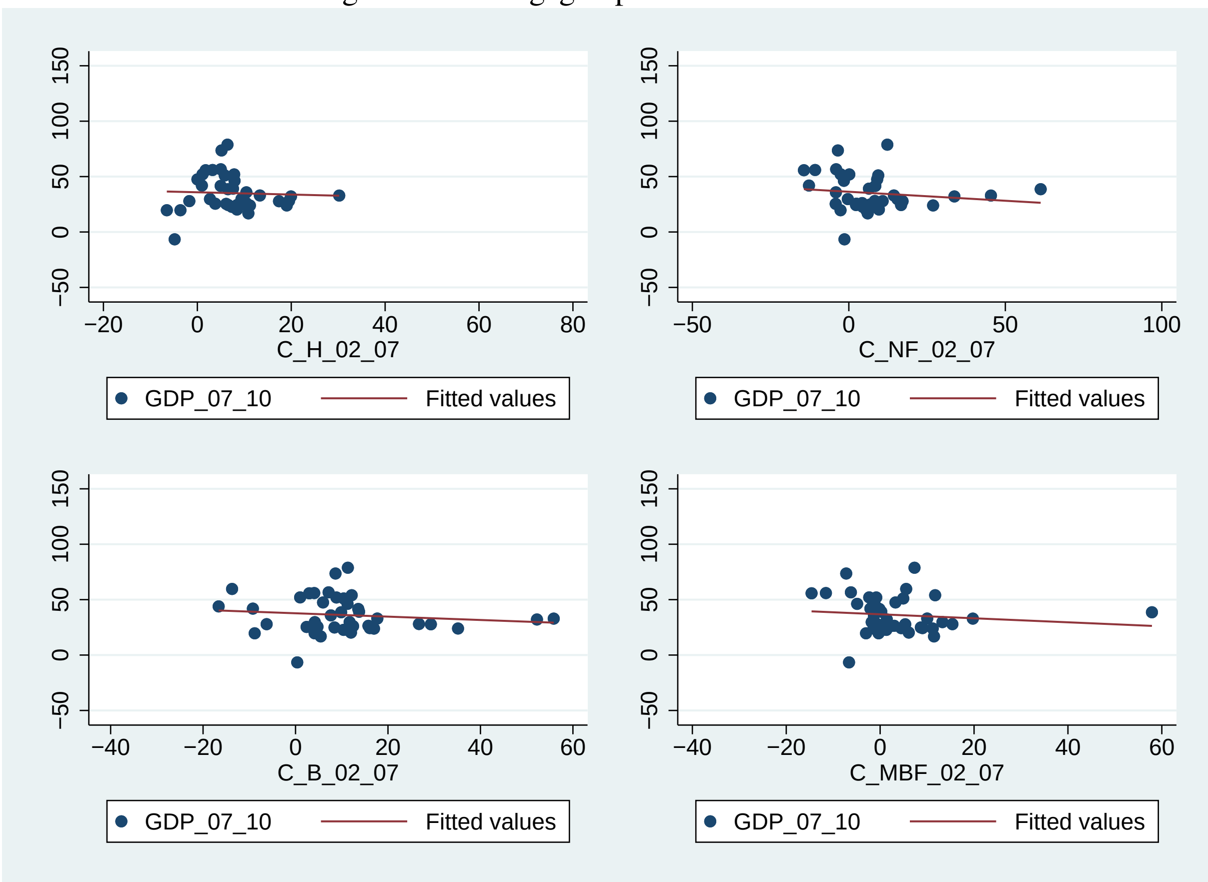
Notes: This figure plots the relationship between the change in each of the 4 credit/debt variables from 2002 to 2007, and GDP between 2007 and 2010, for 12 Eurozone countries and Denmark. From top left to bottom right, we have household debt (H), then non-financial firm debt (NF), followed by bank credit (B) and ending in market based finance (MBF). This is an illustration of the results obtained in columns 1 and 2 of Tables 2.6 and 2.7.

Figure 2.5: Sovereign Spread Convergence in the Eurozone: IV estimation



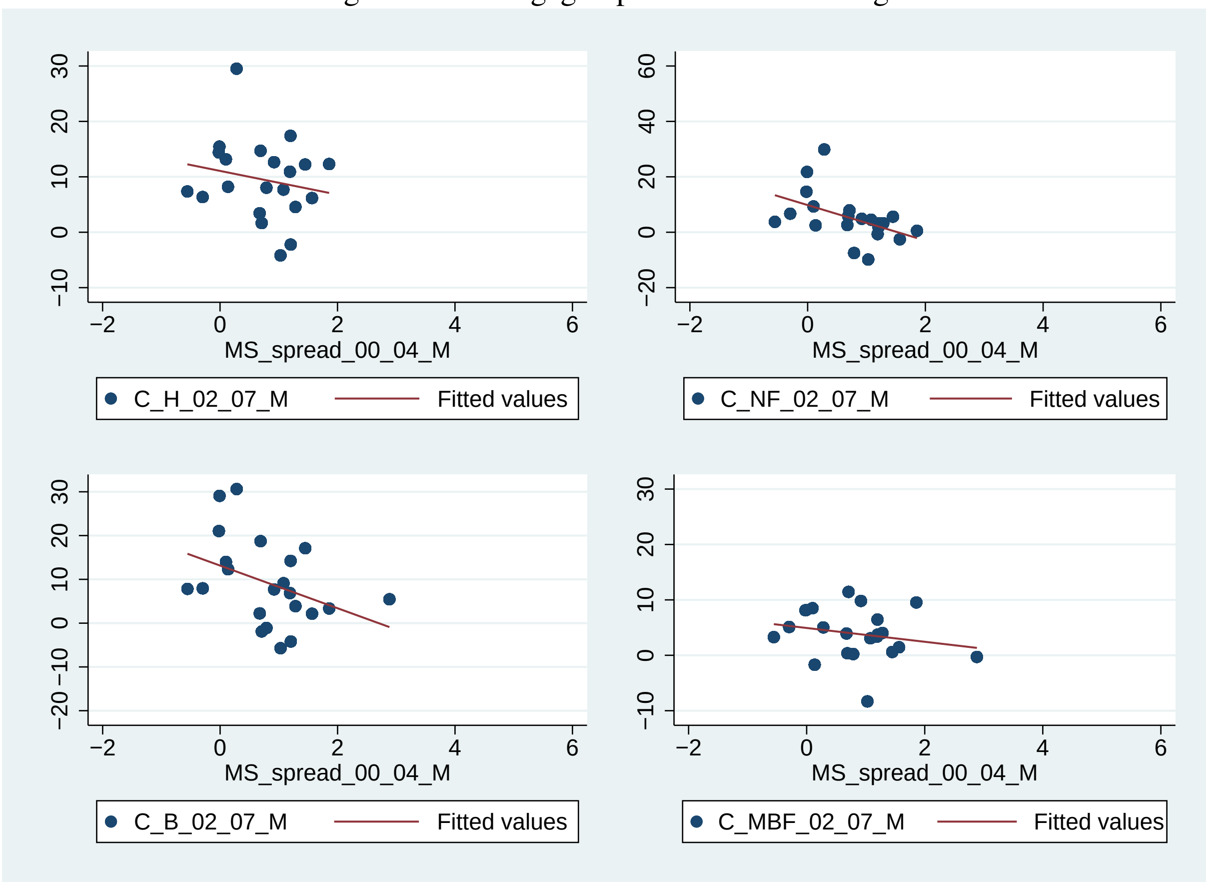
Notes: This figure plots the relationship between the change in each of the 4 credit/debt variables from 2002 to 2007, and GDP between 2007 and 2010, for 12 Eurozone countries and Denmark. From top left to bottom right, we have household debt (H), then non-financial firm debt (NF), followed by bank credit (B) and ending in market based finance (MBF). This is an illustration of the results obtained in columns 4 and 6 of Tables 2.6 and 2.7.

Figure 2.6: Mortgage Spread: OLS estimation



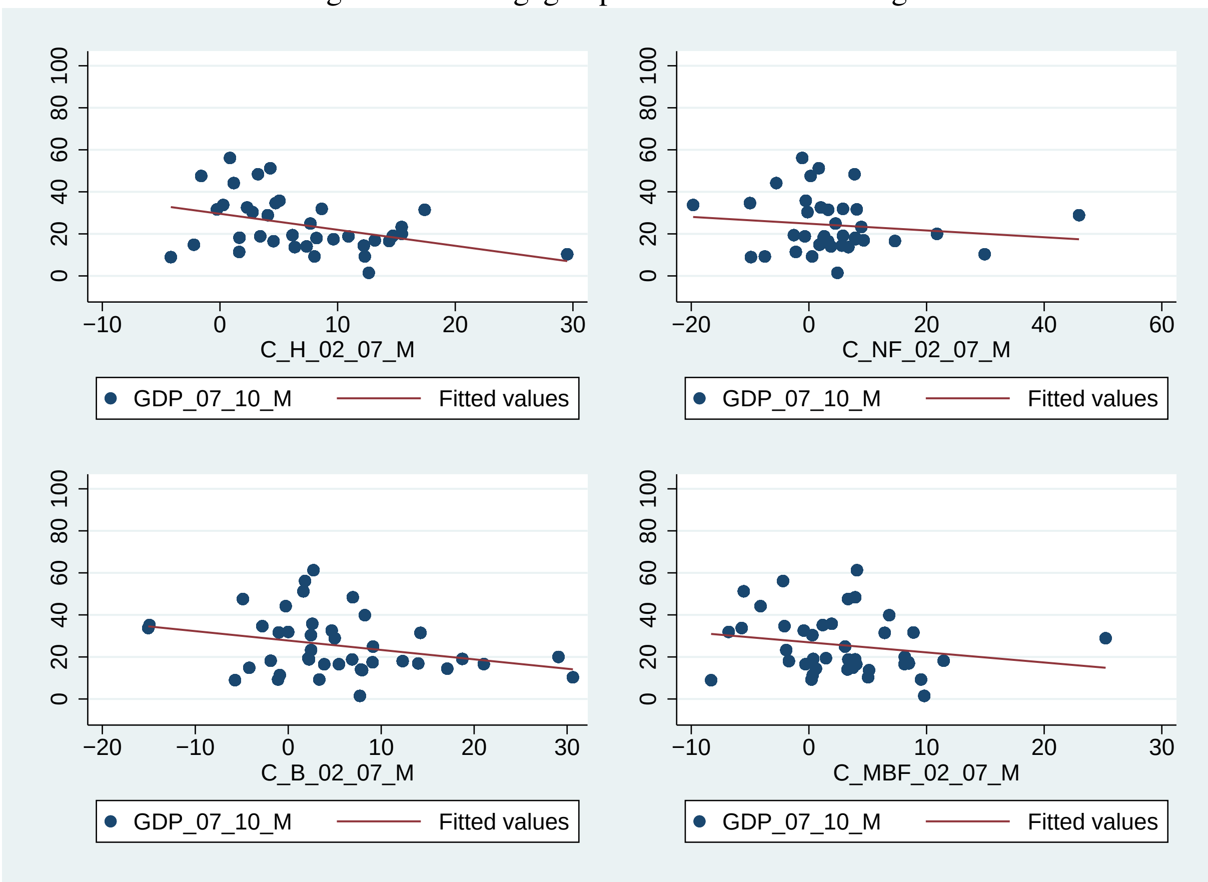
Notes: This figure plots the relationship between the change in each of the 4 credit/debt variables from 2002 to 2007, and GDP between 2007 and 2010. From top left to bottom right, we have household debt (H), then non-financial firm debt (NF), followed by bank credit (B) and ending in market based finance (MBF). This is an illustration of the results obtained in columns 1 and 2 of Tables 2.8 and 2.9.

Figure 2.7: Mortgage Spread: IV - First Stage



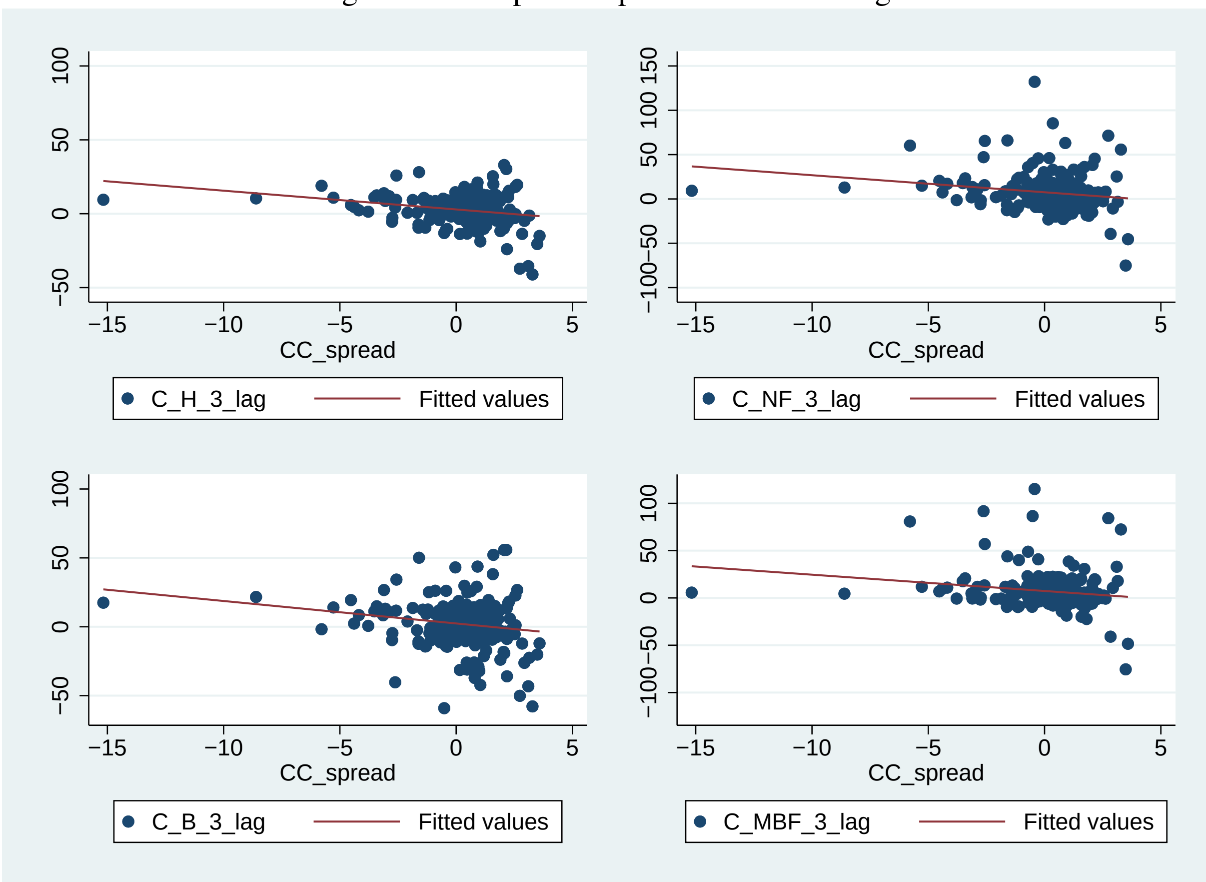
Notes: This figure plots the relationship between the change in the mortgage lending rate relative to the 10-year government bond yield between 2000 and 2004, and change in each of the 4 credit/debt variables from 2002 to 2007. From top left to bottom right, we have household debt (H), then non-financial firm debt (NF), followed by bank credit (B) and ending in market based finance (MBF). This is an illustration of the results obtained in columns 3 and 5 of Tables 2.8 and 2.9.

Figure 2.8: Mortgage Spread: IV - Second Stage



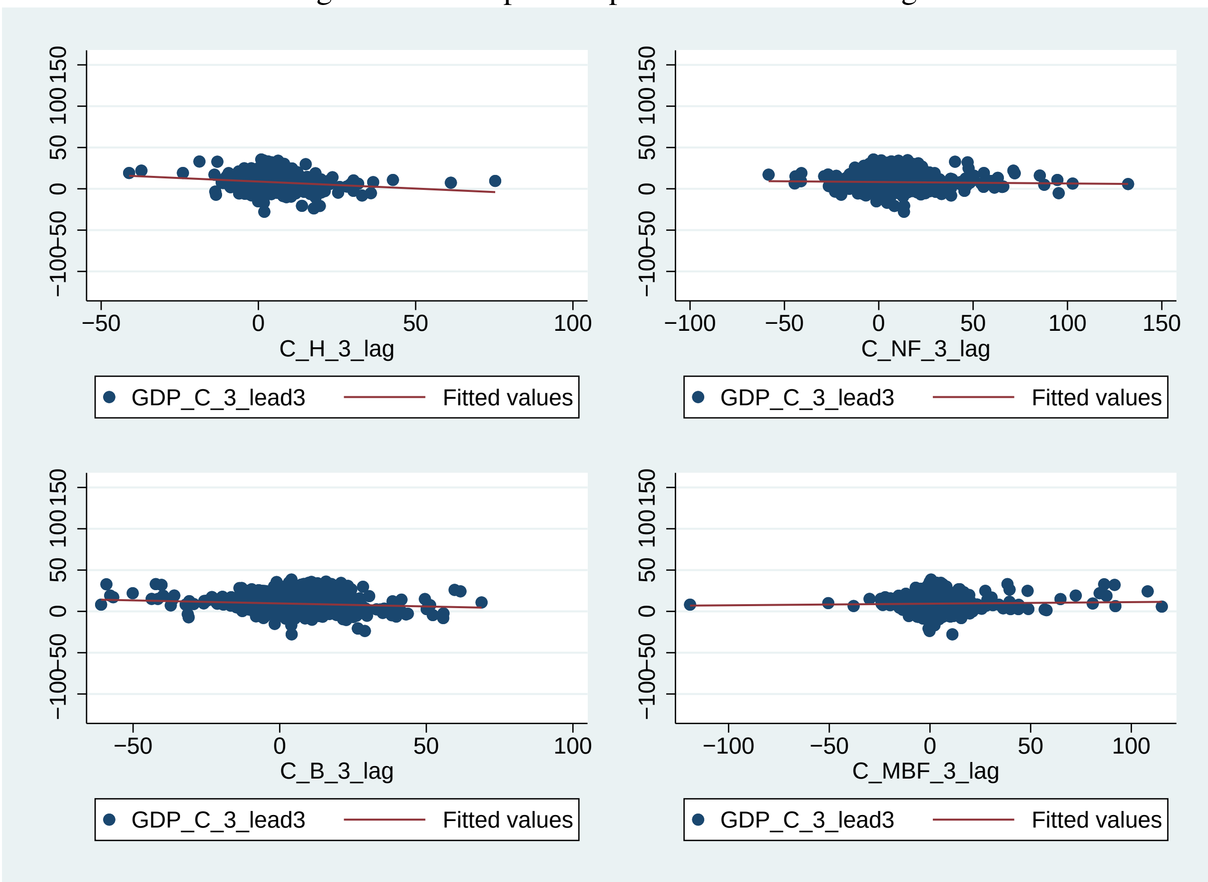
Notes: This figure plots the relationship between the change in each of the 4 credit/debt variables from 2002 to 2007, and GDP between 2007 and 2010, which corresponds to the Second Stage in the IV estimation. From top left to bottom right, we have household debt (H), then non-financial firm debt (NF), followed by bank credit (B) and ending in market based finance (MBF). This is an illustration of the results obtained in columns 4 and 6 of Tables 2.8 and 2.9.

Figure 2.9: Corporate Spread: IV - First Stage



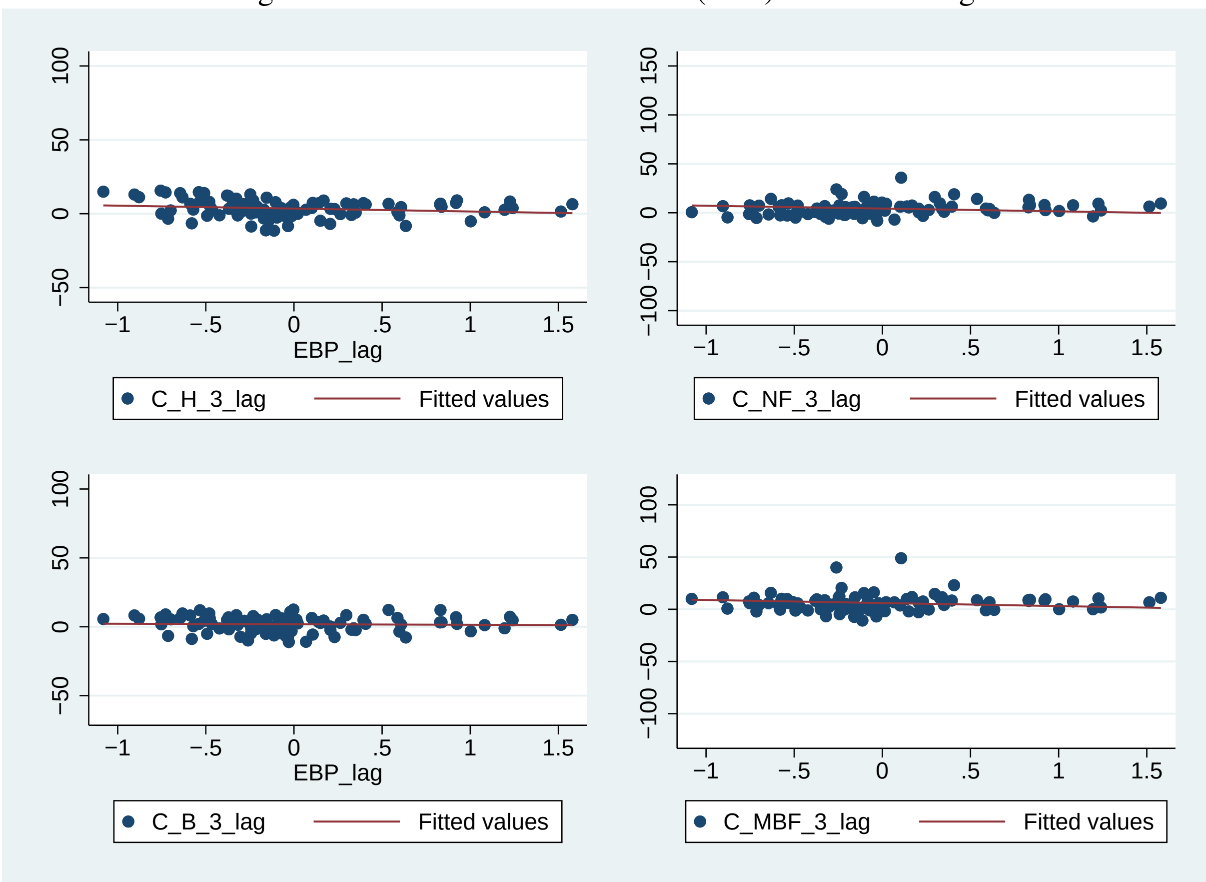
Notes: This figure plots the relationship between the change in the corporate lending rate relative to the 10-year government bond yield, and change in each of the 4 credit/debt variables. From top left to bottom right, we have household debt (H), then non-financial firm debt (NF), followed by bank credit (B) and ending in market based finance (MBF). This is an illustration of the results obtained in columns 5 and 7 of Tables 2.10 and 2.11.

Figure 2.10: Corporate Spread: IV - Second Stage



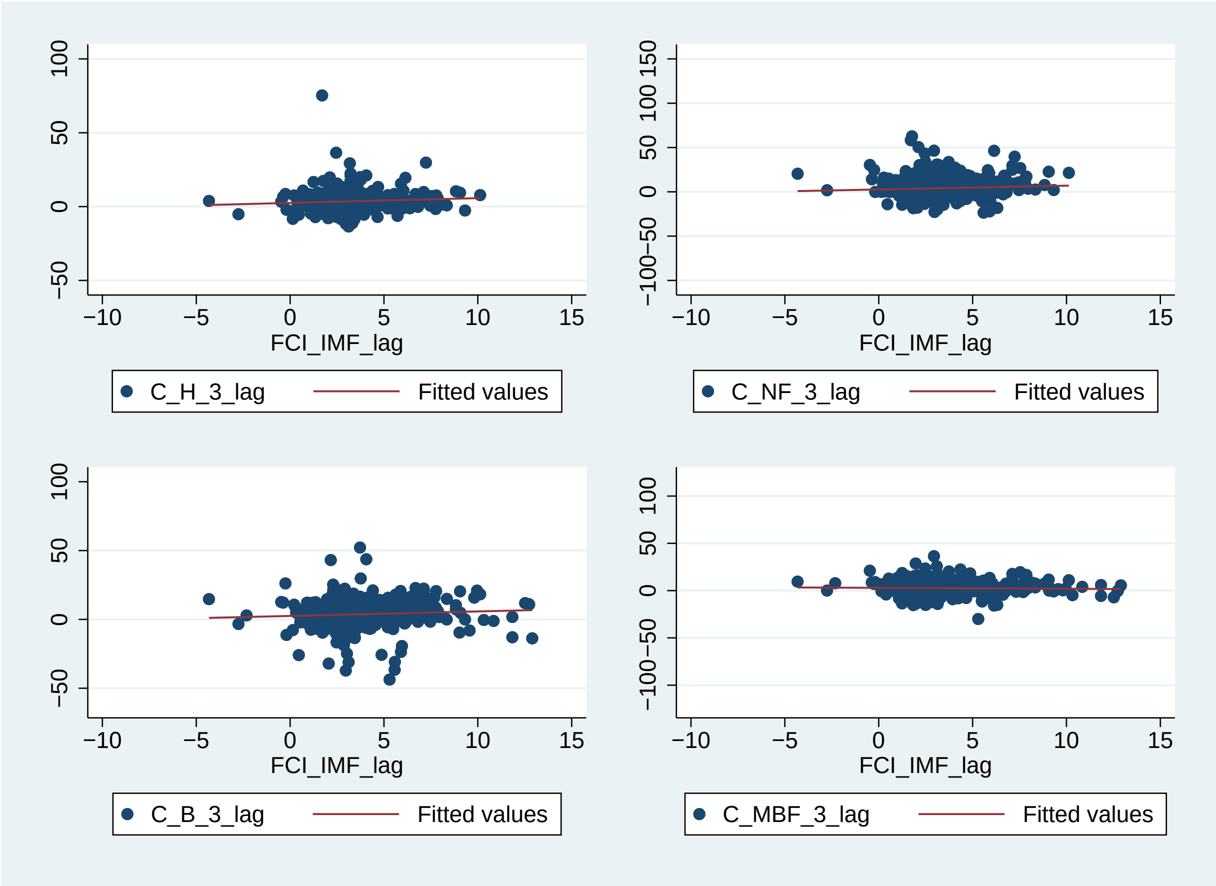
Notes: This figure plots the relationship between the change in each of the 4 credit/debt variables, and GDP growth, which corresponds to the Second Stage in the IV estimation. From top left to bottom right, we have household debt (H), then non-financial firm debt (NF), followed by bank credit (B) and ending in market based finance (MBF). This is an illustration of the results obtained in columns 6 and 8 of Tables 2.10 and 2.11.

Figure 2.11: Excess Bond Premium (EBP): IV - First Stage



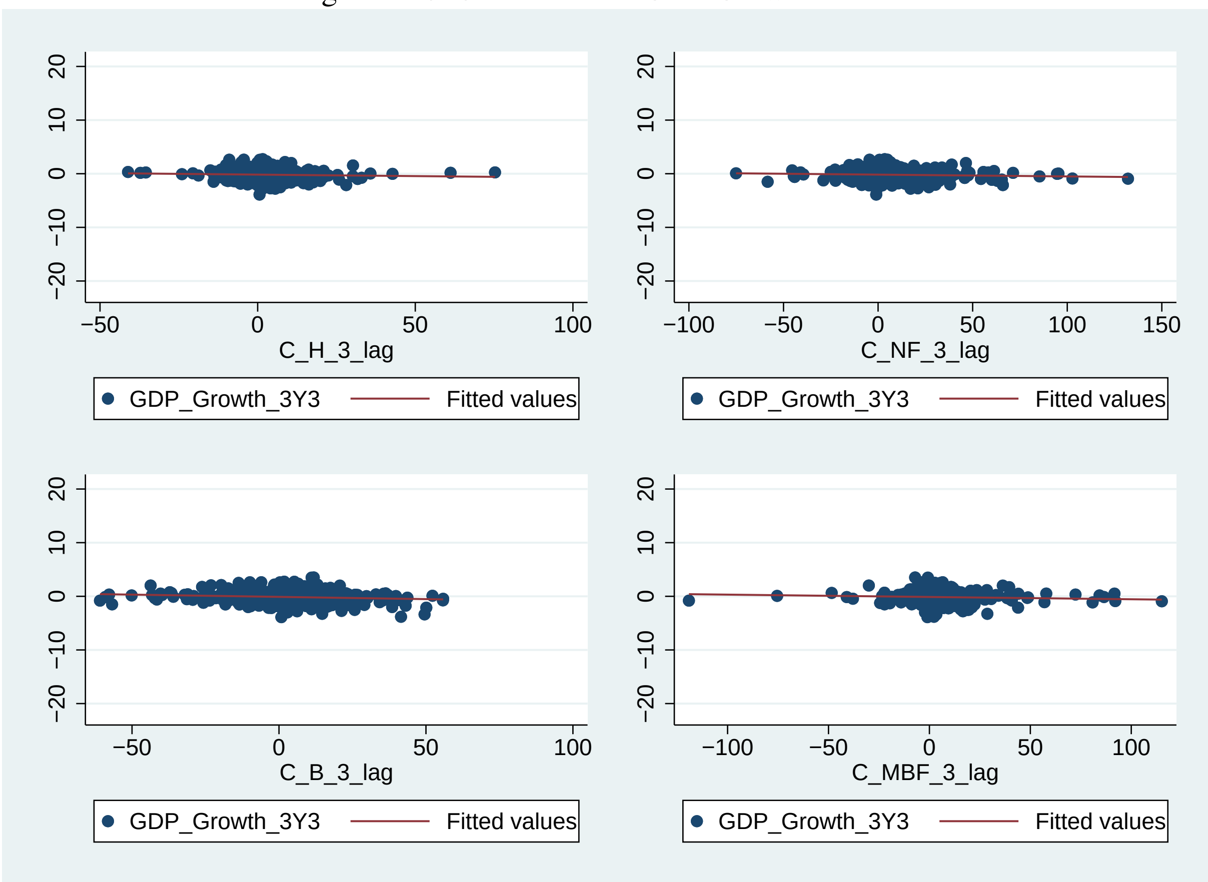
Notes: This figure plots the relationship between the lagged Excess Bond Premium (EBP), and change in each of the 4 credit/debt variables. From top left to bottom right, we have household debt (H), then non-financial firm debt (NF), followed by bank credit (B) and ending in market based finance (MBF). This is an illustration of the results obtained in columns 1, 3, 5 and 7 Table 2.12.

Figure 2.12: Financial Conditions Index (FCI): IV - First Stage



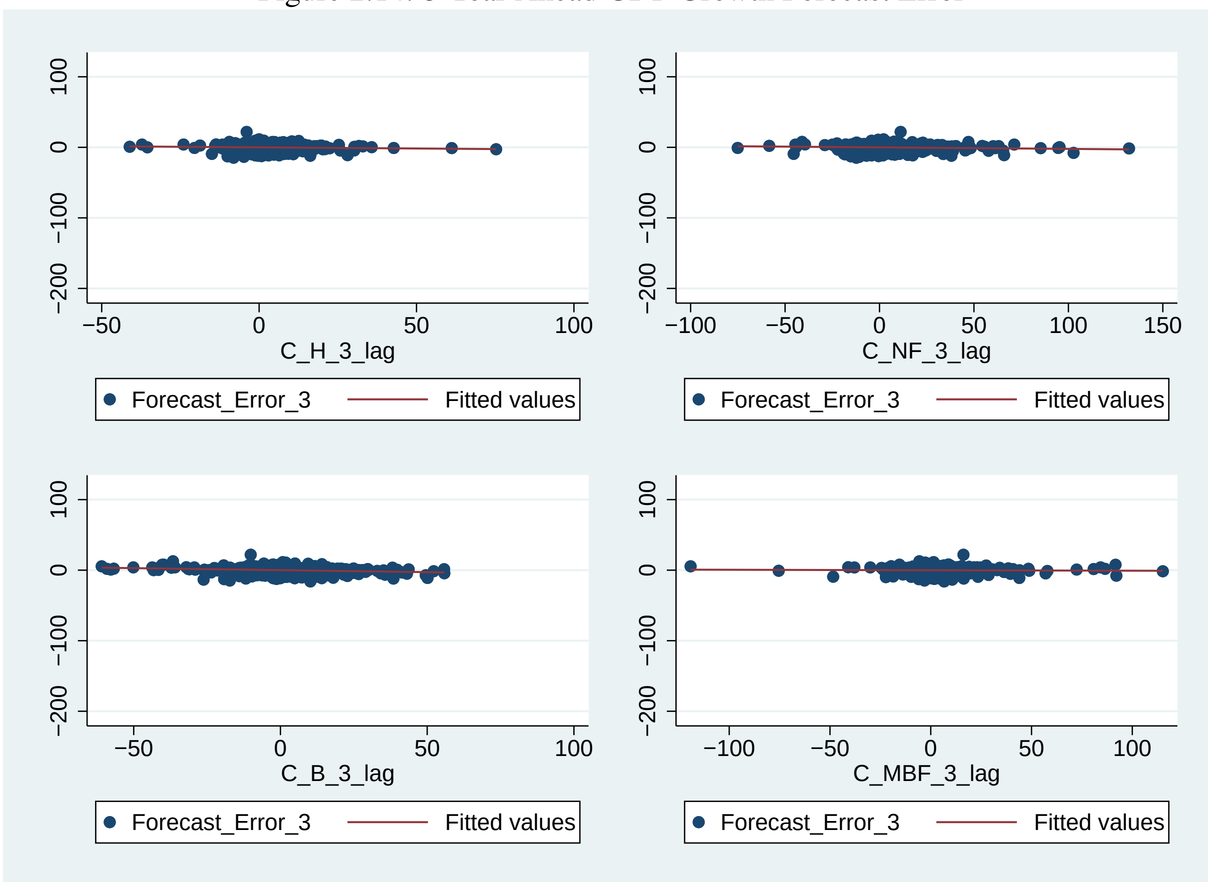
Notes: This figure plots the relationship between the Financial Conditions Index (FCI), and change in each of the 4 credit/debt variables. From top left to bottom right, we have household debt (H), then non-financial firm debt (NF), followed by bank credit (B) and ending in market based finance (MBF). This is an illustration of the results obtained in columns 1, 3, 5 and 7 Table 2.13.

Figure 2.13: 3 Year Ahead GDP Growth Forecast



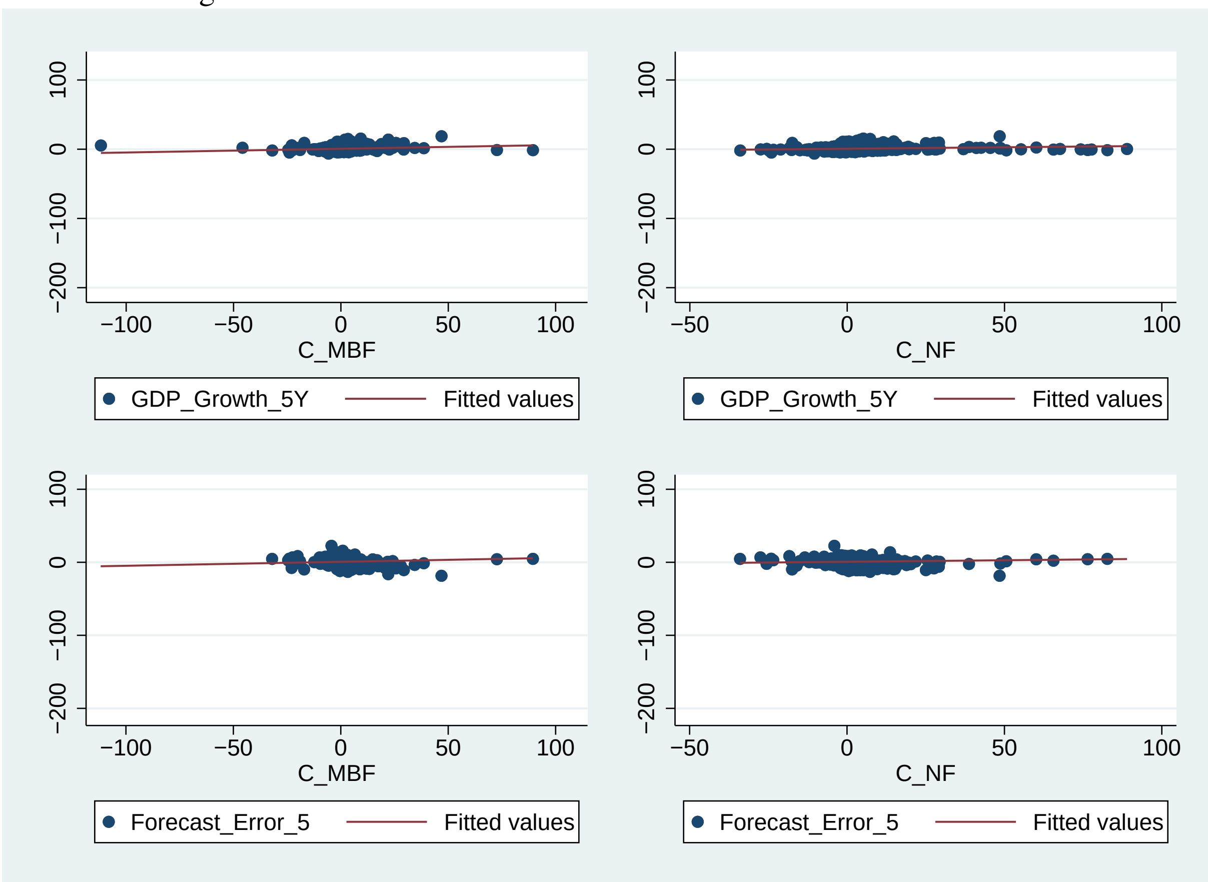
Notes: This figure plots the three-year ahead GDP forecasts against the change in each of the 4 credit/debt to GDP variables, from t-4 to t-1. From top left to bottom right, we have household debt (H), then non-financial firm debt (NF), followed by bank credit (B) and ending in market based finance (MBF).

Figure 2.14: 3 Year Ahead GDP Growth Forecast Error



Notes: This figure plots the three-year ahead GDP forecast error against the change in each of the 4 credit/debt to GDP variables, from t-4 to t-1. From top left to bottom right, we have household debt (H), then non-financial firm debt (NF), followed by bank credit (B) and ending in market based finance (MBF).

Figure 2.15: 5 Year Ahead GDP Growth Forecast and Forecast Error



Notes: This figure plots the five-year ahead GDP forecast and forecast error against the change in the market based finance (MBF) and the non-financial firm debt to GDP variables, from t-6 to t-1. The top graphs refer to the GDP forecast, while the bottom graphs refer to the GDP forecast error.

Chapter 3

Asset vs Income: How constraints impact productivity and debt structure

3.1 Introduction

Financial frictions play a central role in the economy, by constraining the firm's ability to resort to borrowing funds. [Diamond and Dybvig, 1983] are among the first papers to point out the importance of this characteristic, by pointing out the vulnerability of the financial system to bank runs, and it's potential self-fulfilling component. [Gertler and Gilchrist, 2018] provide a summary of the contribution of research incorporating market frictions, how they may generate financial crisis and how it can be transmitted to the real sector. On the other hand, the imposition of financial constraints can also have an advert effect on economic growth, by limiting firm's access to additional funds, impacting their productivity, and reducing their investment and profitability.

Traditionally, the literature has simplified the modelling of the debt capacity of the firms according to their market leverage[1]. However, in reality, the firms can have different explicit constraints on the amount of borrowing, or even a combination of different constraints, which can be very different from establishing a maximum for the market leverage. We consider the impact of borrowing constraints through loan covenants, which consist of provisions in debt contracts that constrain future lending. They circumscribe a set of actions a borrower may take (nonfinancial covenants) or specify minimum or maximum thresholds for cash flows or balance sheet variables (financial covenants). In our case, mostly due to data availability and summarizing purposes, we focus on the role of financial constraints. Thus, the choice for the different characteristics associated with the constraints are likely to yield different impacts, including the amount, maturity, interest rate charged, type of covenant(s) and variables chosen, limits set, and stipulation of covenant violation. In the case where a borrower either is unable or chooses not to comply with the covenant, they enter technical default and the lender is able to accelerate

[1] Recall the financial accelerator component in [Bernanke and Gertler, 1999] that we discussed before.

the repayment of the loan, force renegotiation of the loan, or waive or reset the covenant with no further impact on the loan. In the case of this chapter, we group the different covenants into 3 main groups: Interest coverage (IC), Debt-to-earnings (DE), and Leverage (LEV), with a particular focus on the Interest coverage (IC) and Leverage (LEV) covenants. Even though IC covenants, and especially financial covenants in general, are very common, there are still significant uncertainties that remain about how the structure of these covenants/constraints influences macroeconomic dynamics. In this paper, we evaluate how the different functional forms of these covenants can affect productivity and the borrowing structure of the firms.

To motivate our topic, we construct a dataset at the firm-year level by merging the syndicated loan data, provided by Refinitiv LPC DealScan ("DealScan"), with the firm level data, provided by the Center for Research in Security Prices (CRSP)/Compustat Merged Database ("CCM"). In terms of number of facilities/loans, we have a total of 171,752 different facilities that originated between 1982 and 2022. Of the firms which contain information regarding the covenants associated to the loans, around 76% include IC covenants, and around 18% include LEV covenants. This would match the composition of datasets in similar papers. [Lian and Ma, 2021] combine different data sources, and show that only 20% of credit to US firms is asset-based, while 80% is earnings-based. [Greenwald, 2019] focus on constraints where the interest payments are restricted by earnings, which are often associated with earnings-to-debt restrictions (these would be the Interest Coverage(IC) constraints that we have discussed). They also calculate that they are present in over 80% of firms with covenants. Thus, we consider that there is a significant overlap (or similarity) between the IC covenants and earnings-based constraints.

We conduct an analysis on firms subjected to different covenants, and find that firms with earnings-based constraints have lower levels of TFP (Total Factor Productivity), and short-term debt, when compared to firms with asset-based constraints. The data also shows that this is connected to an additional negative impact that short-term debt has on the productivity for the firms with earnings-based constraints, which does not verify in the firms with asset-based constraints. Both these characteristics are robust to the use of 3 different TFP estimation methods, different subsamples, and additional controls, including age and size of the firm. Other characteristics, including total assets, or long-term debt, seem to be caused by differences in the size of the firms, and not due to the different covenants.

Thus, we consider a quantitative dynamic stochastic partial equilibrium model, with three main types of firms, which explores the impact of short-term and long-term borrowing on firm's balance sheets, on the different variables, subjected either to earnings based or collateral constraints. We construct replications for this theoretical model, and assess how well it fits our actual data.

The structure of the paper is as follows. Section 3.2 provides the motivation for the topic we are studying, as well as some data which supports the framework of our model. Section 3.3 reviews the relevant literature related to our topic. Section 3.4 describes the main components of the model, starting with a timeline of the different events, and describing additional information for each of the decisions of the firms. Section 3.5 presents the calibration of the different parameters used to estimate our model. Section 3.6 discusses the results obtained. Section 3.7 provides the conclusions of this paper.

3.2 Data Construction and Motivation

3.2.1 Description of the raw datasets and the code

We construct a dataset at the firm-year level by merging the syndicated loan data, provided by Refinitiv LPC DealScan ("DealScan"), with the firm level data, provided by Center for Research in Security Prices (CRSP)/Compustat Merged Database ("CCM"). We resort to the Dealscan data mainly for information on the different covenants associated with the syndicated loans, and use it to allocate the firms to 3 main different covenant categories. Additionally, we also retrieve information on a quantitative level (deal amount, tranche amount, EBITDA, fees, and others), as well as on a qualitative level (market segment, primary purpose, seniority type, etc). All the information was obtained from Wharton Research Data Services ("WRDS").

DealScan is one of the most commonly used sole lender and syndicated loan market databases, due to its extensive content and relatively easy access and availability. The current coverage includes loans originated as early as 1981 and the database is updated frequently. This database identifies loan originations from borrower SEC filings, arrangers and other lenders, and various public sources. The information on loan pricing and covenants is collected from origination. For some of the loans, there is also information on the participants, and the borrowers' balance sheet data. In the case of private borrowers, however, this may not be the case.

S&P Global Market Intelligence CRSP/Compustat ("CRSP/Compustat") is a commercially available database of publicly listed company filings. The current coverage includes annual company filings starting from 1950 and quarterly statements starting from 1960. The main information contained in this database consists of balance sheet, income statement, cash flow, and additional supplemental data or miscellaneous items. CRSP/Compustat data standardize the reporting across items and filing types, and includes primarily publicly listed company information, which narrows the scope of the data sample when matched to loan-level sources. It contains debt data for different horizons (short-term and long-term), albeit not having specific indicators for "bank debt". It additionally has information on borrower health and ability-to-repay when combined with loan level datasets.

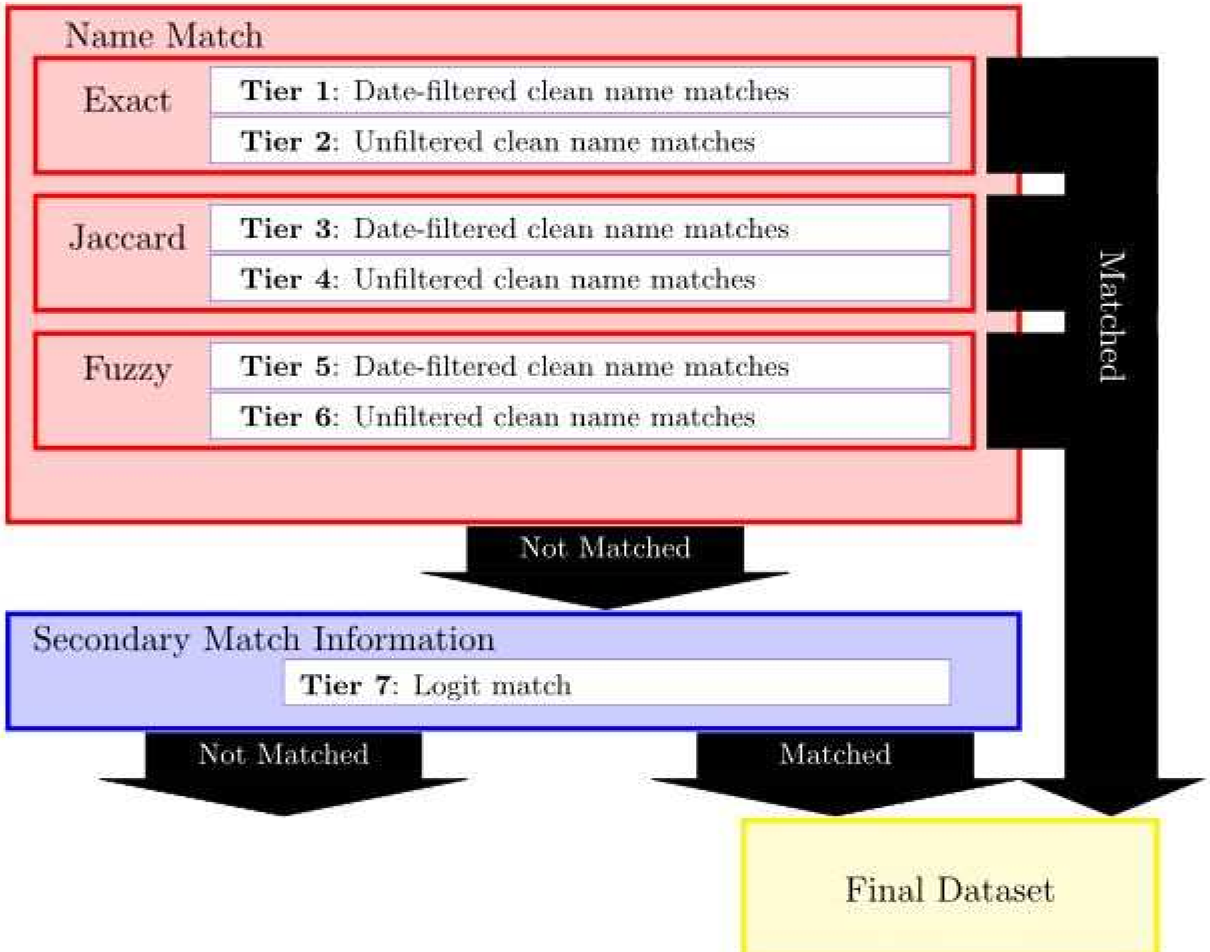
In order to establish the connection between the 2 datasets, we resort to the code provided in [Cohen et al., 2021][2]. In this paper, the authors introduce a general method for determining linkages to different datasets without common identifiers, and they apply to a specific

[2]The code is available at https://github.com/seunglee98/ds_cs_fedmatch. I would like to thank Christopher Webster and Blake Marsh at the Federal Reserve for their assistance in understanding the code.

scenario, linking 3 main datasets: Refinitiv LPC DealScan, S&P Global Market Intelligence CRSP/Compustat, and National Information Center Structure Data. In our case, we just link the first 2. While CRSP/Compustat contains the firm-level information, Dealscan contains information at the package and facility level associated with those firms at origination of the loans. Traditionally, other authors have resorted to the linking procedure provided by [Chava and Roberts, 2008]. We opted for the described alternative instead for the following reasons: 1 - even though the [Chava and Roberts, 2008] linking procedure has been provided and been updated periodically, the methodology that we apply allows us to include more up to date information (the last update was on April, 2018, while we can include all the available information between 2018 until 2022) Therefore, we would not need to wait for an update of the traditional linking procedure, if we were looking for more recent information; 2 - The code also compares the matching results with the linking information of [Chava and Roberts, 2008]. Therefore, the information is, not only, taken into account, to confirm the accuracy of the results of the code we use, but also to compare in terms of which linking procedure performs best; 3 - the matching procedure that we apply can also be used to link other datasets, beyond the scope of syndicated loans, matching more generic string datasets from different sources for a common business entity.

The methodology for the initial dataset linking between Dealscan and CRSP/Compustat is described in Figure 3.1, using a four-stage matching method. The authors start by using string cleaning functions on the firms' names. These procedures constitute of minor changes to standardize the company names across the different datasets, in order to more easily identify true matches. They proceed with using the information on the companies' names to connect the information across the 2 datasets using the first 3 matching techniques: *exact name matching*, *weighted jaccard*, and the *fuzzy matching*. The last step is using the *logit match*, which takes into account, not only, the name information, but also the remaining variables which are present in both datasets (for example, the state where the company is located, the sic code identifying the industry sector in which the firm is included, among others). The final matchscore value is defined according to the matching of the different variables taken into account, and the weights given to each variable.

Figure 3.1: DealScan–Compustat match methodology



Source: Figure 2 in [Cohen et al., 2021].

In each of the first three techniques, the authors also resort to the different variables that contain information on the periods/dates in order to distinguish between matches with higher and lower confidence. More specifically, a filter is applied to remove any matches where the start date of a specific facility/tranche of the specific deal is not within the first and last period of the company record in CRSP/Compustat (obviously, this would constitute an error in either dataset, since it would imply that a certain company/firm was part of a facility/tranche within a deal, when there are no records of that firm/company existing during that period). Given that companies change names on a rather frequent basis, and these changes are not always updated in both datasets, it is likely that some of observations will not be considered due to incorrect information in terms of the periods, but also simply due to the name changes not being updated in one of the datasets. Thus, the matches using this filter (the tier 1 matches) can be described as being of the highest quality within each technique. Nonetheless, we also keep the matches without the filter (the tier 2 matches), which we classify as the unfiltered matches.

The 4 different matching techniques described in Figure 3.1 are ordered in terms of match quality, credibility and/or requirements for the match, which is also the order that is followed in the code. This would imply that the matches found with the exact name matching technique would be of the highest quality, since there would need to be an exact match between the company's name, and just small differences between the names would avoid the match. Then, the weighted jaccard matches are considered to be the next highest quality matches, since the firm's names are allowed to have some differences (in terms of the strings that compose those names), but only allowing small differences (under the tolerance criterion defined). This is followed by the fuzzy matches, which allows more differences between the strings of the firm's name than the weighted jaccard, but still with significant quality, given the tolerance levels that were set[3].

The last matching technique is the logit match, and is only applied to the observations that were not matched within all the previous 3 methods. Notice that this is treated separately in Figure 3.1, as well as in the code. There are 2 main reasons for this: 1 - this technique uses additional variables to the company's name for the matching, including the industry sector (in the form of the SIC code), as well as the location (in terms of the state); 2 - there is a higher difference in terms match quality between the logit match and the previous 3 matching techniques. The quality here is considered to be lower due to there being lower heterogeneity and uniqueness between the additional variables that are taken into account. For example, the SIC codes are able to identify the industry group, but many different firms would be part of the same industry group. The same reasoning can be applied to the state/location information. To define the matches, the authors resort to a numeric distance on the different variables used for the matching, which are different for each field: Jaro–Winkler string distance for names and indicators for all other variables.

In order to estimate the similarities between the different potential matches, the authors start by generating a separate dataset, which takes 1 million drawn pairs of observations from DealScan and Compustat. Then, they test each pair for potential matching, using the Facility ID+ Firm ID combinations that are also available in [Chava and Roberts, 2008], and estimate the logit model according to the results, using variables that are present in both DealScan and CRSP/Compustat datasets as the explanatory variables. The interpretation of the coefficients is relatively straightforward: it reflects how each of these variables is useful to predict a match between the datasets. The larger the value of the coefficients, the better they are for being used to predict a possible match.

3.2.2 DealScan–Compustat match results

In order to preserve the majority of the data in the initial DealScan dataset, we include the loans to all US borrowers (according to the country identifier), with origination dates after 1980 (any

[3]The matches kept in the dataset are such that the Jaccard distance is not higher than 0.05. The Jaro-Winkler penalty parameter is set at p = 0.1. This is set in the original code, and we keep the original calibration.

loans with the origination date before 1980 are dropped from the sample, since it is likely that they results from errors in the data).

We have an overall analysis of the initial dataset in Table 3.1. We have obtained a total of 501,449 observations, which constitute the different combinations of the different companies, different deals, different tranches within the deal, and the different matching techniques used. From these, a total of 368,244 stem from the exact name matching method (around 73.43%), 62,436 stem from the weighted jaccard method (around 12.45%), and 70,769 stem from the fuzzy matching method (around 14.12%).

Table 3.1: DealScan–Compustat match methodology

Matching technique	matches	matches (%)	Tier 1	Tier 1 (%)	Tier 2	Tier 2 (%)
Exact Name Matching	368,244	73.43%	211,126	57.33%	157,118	42.67%
Weighted Jaccard	62,436	12.45%	54,089	86.63%	8,347	13.37%
Fuzzy	70,769	14.12%	61,114	86.36%	9,655	13.64%
All	501,449	100%	326,329	65.08%	175,120	34.92%

Notes: In this table, we provide the total number of matches, which were identified according to each matching technique. We also have the matches identified using the filter (Tier 1), and unfiltered (Tier 2). Finally, we also calculate the proportion of the matches for each case.

Notice that the vast majority of the matches in our sample are from the exact name matching method (almost 3 in every 4 matches), which is the matching technique with the highest requirements, and gives the highest quality matchings, almost guaranteeing, with 100% certainty, a true match (a matching between 2 sets which is correct), and rejecting a false match (a match between 2 sets which results from a mistake of the matching technique), since, with this methodology, a match would only happen if the names between the datasets are an exact match. The only possibility for any errors would be due to the initial data cleaning procedures that are applied before the matching techniques. However, these cleaning procedures are very mild, thus, safekeeping the quality of these matches.

Not only that, this would constitute the lower bound in our initial dataset. Recall that we have all the matches identified in our dataset using the different matching techniques, which would imply that we could have repeated matches, which are only distinguished in terms of the matching technique. In other words, we could have the exact same match identified by all the different techniques. In order to avoid having repeated observations in our dataset, we keep only one of the methods, and drop the repeated matches found for the remaining methods. Given that the matching techniques are ranked in terms of quality, credibility and/or requirements for the match (that is, initial matching techniques, like the exact name matching will have higher requirements for a match, while the fuzzy matching will have lower requirements, but will allow us to identify more matches that were not identified by previous techniques), with the exact name matching method being the highest quality matching technique, we keep all the matches identified by the exact name matching technique, and drop the observations that identified those same matches with the different techniques. For matches that were not identified using the exact name matching technique, we give priority according to the ranking (keeping those were the highest ranking was the weighted jaccard, and only saved the matches with the fuzzy matching in cases where this methodology was the sole identified of the match). Therefore, this would imply that, in the final dataset, we will have a higher % of matches identified using the exact name matching method (at the lowest, they will be the same 73.43%, for the case there are no repeated matches, in which case, all the different matching techniques only identify different matches).

As for the difference between filtered (Tier 1), and unfiltered (Tier 2) matches, most of the matches that we have in the dataset are from Tier 1, implying higher quality in the matches obtained. For the name matching, it is relatively even, although with a small difference towards the Tier 1 matches (57.33% in Tier 1 vs 42.67% in Tier 2). But for the remaining matching techniques, the difference is much higher in favour of Tier 1, with more than 85% of matches contain the application of the filter, and only less than 15% are unfiltered. This guarantees a high quality for the overall matches obtained. Since the exact name matching is the matching technique with the highest quality, even the unfiltered matches obtained would fall under the category of high quality. And as the quality of the matching techniques decreases with the other 2 methods, quality is guaranteed through the higher proportion of the matches obtained with the filter[4].

As far as the logit matching, we start by showing the estimated coefficients from the logit regression using the [Chava and Roberts, 2008] dataset to confirm the matches, in Table 3.6, in the appendix. It includes the coefficients estimated for the different criteria used for the matching, which are the name (according to the Jaro–Winkler distance between the names), the state where the firm holds the headquarters, and the industry in which the firm's business is included, as well as the standard deviations and significance levels. Clearly, the name match indicator is the best predictor out of the three indicators, given by the dimension of the coefficient, which gives additional credibility to the decision to choose the companies' names as the main indicator used for the previous 3 matching techniques. And although the coefficients for the state and industry indicators are lower, they are still positive and statistically significant, increasing the match probability when they are taken into account. We proceed by resorting to these estimated coefficients obtained from this sample in order to find matches in the overall database. For each case, the match probability will be calculated, and we will only keep matches above a 90%

[4]Just to clarify, the values in the table for the Tier 2 correspond to the additional matches that were not identified by Tier 1, in the same reasoning we used for the matches of the different matching techniques. Since the Tier 2 matches have less constraints compared to the Tier 1 (due to the filter), the overall matches identified by the Tier 2 will always be higher (or, at most, equal) to the Tier 1 matches.

match probability.

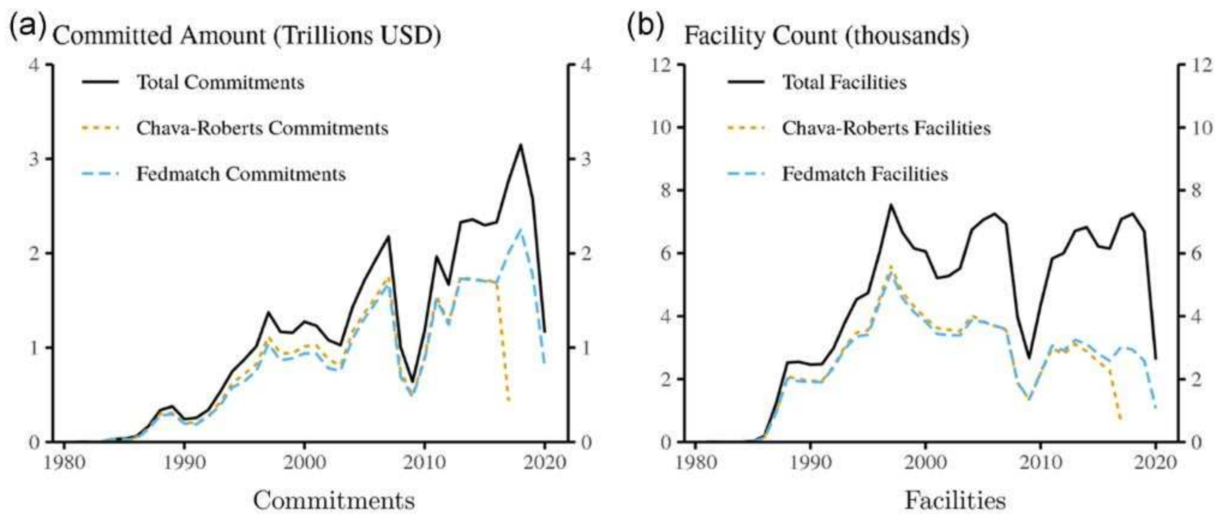
Notice that, so far, we have not described the number of observations with the logit function matching in our dataset. The reason is that none of the matches found by the logit function has been kept in our dataset. Instead, all of them were identified through the other 3 matching techniques. There are 2 reasons for this outcome: 1 - All the matches identified by the logit function were also identified by the previous 3 matching techniques. In that case, the same matches would not be added to the dataset, as the code would give preference to the higher quality techniques for that identification; 2 - The remaining matches that were only identified by the logit function, and not identified by the other previous 3 matching techniques, do not meet the 90% match probability mentioned above.

Our results in Table 3.1 can be directly compared with those obtained by [Cohen et al., 2021] (see Figure 4 in their paper). The authors provide even more detail in their results, including a time series component on the matching over the years. They show that, over the years, there is relative consistency in the number of matches identified for the different matching techniques, with the exact name matching identifying between 60% and 65% of the total matches, the weighted jaccard identifying between 30% and 35% of the total matches, and the fuzzy matching identifying around 4% of total matches. The main changes are in terms of the filter vs unfiltered matches within the exact name matching. There is an increase in the proportion of the filtered matches, compared to the unfiltered matches, reflecting an increase in the quality of the matches found over the years. The authors point out that, the main reason for the exact name matches in initial years being unfiltered is due to limitations in the historical data. As in our case, the majority of their matches are from the exact name matching technique, with a higher proportion for the filtered matches within the exact name. They also have no matches (or almost none) identified through the logit match (the reasoning being the same as in our case, described in the previous paragraph). There are also some differences that we are able to identify: 1 - the proportion of the exact name matching in terms of total matches is a bit higher in our dataset (between 60% and 65% in their case, compared to 73.43% in our case); 2 - the proportion of the unfiltered matches within the exact name matching technique is higher in our dataset (31.13% in our dataset compared to between 5% and 10% in their case); 3 - the proportion of the weighted jaccard matching in terms of total matches is lower in our dataset (12.45% in our dataset, compared to between 30% and 35% in their dataset); 4 - within both the weighted jaccard and the fuzzy matching, most of our matches are filtered matches, while most of them are unfiltered in the original dataset. These differences can mainly be attributed to the matches for more recent periods. It would seem that most of them would fall into the unfiltered exact name matching, while some of them would also fit into the filtered weighted jaccard and fuzzy matching.

In terms of number of facilities, in our case, we have a total of 171,752 different facilities that originated between 1982 and 2022. This compares with 177,013 facilities obtained in [Chava and Roberts, 2008], and the 138,369 facilities obtained by [Cohen et al., 2021].

The facilities (or tranches) correspond to the different number of loans. The match is accomplished by linking a loan's facility id (using the facilityid or facid variable) in Dealscan to a borrower's unique company identifier in Compustat (using the GVKEY variable). The number of loans/facilities/tranches is higher in our sample than in the original code, likely due to taking into account more recent periods, but still a bit below the ones obtained by [Chava and Roberts, 2008]. When comparing the matches obtained, in terms of commitments amount and facility count over different years, between [Cohen et al., 2021], [Chava and Roberts, 2008], and all available information, we turn to Figure 3.2.

Figure 3.2: DealScan–Compustat match comparison



Source: Figure 3 in [Cohen et al., 2021]. **Notes**: In Figure 3.2a), we have the total committed amount (in black), the committed amount in the [Chava and Roberts, 2008] matches (the orange dashed line), and the committed amount in the matches of the original code (dashed blue line). Figure 3.2b) follows the same reasoning, but for the number of facilities.

In Figure 3.2a), we can see that the matches in both codes are relatively close to the total amount available in the database, for the years until 2010. After 2010, however, there is a larger difference between the total commitments and the commitments for both codes, but they are still able to incorporate most of the commitments. Overall, the [Chava and Roberts, 2008] find a higher committed amount than the code of [Cohen et al., 2021], but in more recent years, this is clearly reversed. In Figure 3.2b), the same reasoning applies for the number of facilities. The main change from Figure 3.2a) is that there is a higher difference between the total facility count and the number of facilities in the matches of either code (more specifically, starting between 1990 and 2000 until the most recent periods). According to [Cohen et al., 2021], this is a reflection of smaller and nonpublicly listed companies increasingly resorting to syndicated loans for financing around this time. However, given that the information in CRSP/Compustat is mainly from publicly listed companies, it is unlikely that matches will be found for these smaller nonpublicly listed companies. This explanation is reinforced by the evidence that we discussed from Figure 3.2a). Given that the difference in terms of committed amount between the total and the matches of the 2 codes is smaller than the difference in number of facilities, which would imply that most facilities that are not included in the matches are with smaller amounts, which are usually contracted by smaller firms.

We did not conduct a more detailed analysis in terms of how the facility matches compare with those of [Chava and Roberts, 2008], for the different matching techniques. However, this information is provided in [Cohen et al., 2021][5], using the same algorithm we apply here. The main reason we did not conduct one ourselves is that it would likely be very similar to the original one, except for the more recent periods, which is information that is also not available in the [Chava and Roberts, 2008] dataset (the file was last updated on 17th of April, 2018, and includes information on facilities between 1980 and 2016). Since the results obtained in [Cohen et al., 2021] already take into account all the data until 2016, the results we would obtain with the same algorithm would be the same. When the authors restrict their sample until 2016, they find 92,688 facilities (or 91,616 if duplicates are removed, where all the duplicate are from the unfiltered exact name matching technique), compared with the 138,369 facilities when they have the full sample. Out of these 92,688 facilities, 81,814 are a match in the [Chava and Roberts, 2008] dataset. This would imply that there is an agreement in facilities/loans identified for 89.8% between the 2 datasets, which gives high credibility to the algorithm that is being used. In terms of the analysis of the matches between matching techniques, the vast majority of the facilities/loans identified through exact name matching (around 95%), are in both datasets, as well as with the weighted jaccard (around 85%), and the logit match (85.7%). The % is even higher for the filtered cases within these methods. For the fuzzy matching, however, the matching is around 50%, meaning half of the facilities/loans were not identified in either one of the datasets. Nevertheless, given the small amount of the total matches identified with the fuzzy matching technique, this has a small impact on the overall sample.

3.2.3 Dataset - DealScan data and covenants

After the matching between the 2 datasets, we moved into retrieving additional information within each of them. We already had some information in the initial matching, including most of the identification for the different companies/borrowers, the deals/packages, and the facilities/tranches/loans, amounts for the deals and the loans, the initial and closing date, industry sector, sales amount, among others.

We begin with the additional data that we retrieved from Dealscan. Given that there have been very recent changes in the Dealscan database[6], which combined all the different Dealscan

[5]See Table 2 of [Cohen et al., 2021] for more detailed information. The authors use the firm ID variable for the matching.

[6]As of August 2021, as it is described at: LoanConnector DealScan Dataset on WRDS

databases into a single one, and changed the identification variables, we resorted to the connection between the old and the new database[7]. We resort to our facilities/tranches/loans variable to make the connection between the 2 datasets, and retrieve the additional data.[8]

Most of the additional information of DealScan that we are interested in is in terms of the debt covenants associated with the loans. For the definition and the grouping of covenants, we resort to the analysis of [Greenwald, 2019]. *Debt covenants set conditions in credit agreements that the firm is obligated to satisfy, as well as the consequences of violation*. There can be many different types of covenants, but, in our case, we are more interested in "financial covenants", that is, covenants which are applied to the financial conditions of the firms. More specifically, the covenants designate that certain firm's variables or statistics (which reflect their financial conditions) are within specific bounds. For example, setting a minimum cash to interest coverage ratio, which would possibly relate to concerns over liquidity. And since these statistics are calculated at a firm level, they restrict the firm's ability to borrow from all possible sources, and not just for a particular loan/facility/tranche.

In the case where the stipulated conditions are not met by the firm, consequences are applied, which, usually, are connected to the credit instrument. For corporate loans, for example, the lender is able to demand immediate repayment of the loan (notice that this is right/possibility, granted to the lender, but not an obligation). Usually, in practice, the lenders do not demand the full repayment, as it would likely be a worse solution for both the lender and the borrower. More specifically, given that it is likely the borrower would not be able to comply with the full repayment, it would declare bankruptcy, and lenders would very likely only be able to collect a relatively small portion of the repayment[9]. Instead, it is in the interest of both parts of the deal to simply renegotiate the terms, for example, in terms of a higher interest rate, or payment of a fee to compensate for the non-compliance of the covenant[10].

Even though covenants do not limit a firm's borrowing amount, and in fact are infringed upon with relative frequency, the infraction is costly for the firms, leading to adverse outcomes, (as explained by [Roberts and Sufi, 2009]). On the study of [Lian and Ma, 2021], it points to firms accumulating resources in order to keep complying with the limits set. This would also

[7] This is also provided at: Thomson Reuters WRDS-Reuters Dealscan

[8] It is important to note that our information is up to date with the new Dealscan database. The only change we needed to make was to add the connection variables for the new database to the final dataset, in order to retrieve additional information. This can be seen, for example, in terms of the time coverage. The old Dealscan database only covers data until 2020, but we have loans that originated in 2021 and 2022 in our initial dataset.

[9] On the other hand, corporate bonds have different consequences, mostly connected to restraining firm's choices/behaviour, for example, for distribution on dividends, or investment. These types of constraints are also addressed in [Chava and Roberts, 2008]. Why do corporate bonds have a different type of covenant, compared to corporate loans? One possible explanation is in terms of the structure on the ownership of these bonds, which is very dispersed. If these covenants are not applied, a dispersed ownership could face difficulties for renegotiation in cases of violation of the terms by the firm. By imposing these covenants, the renegotiation terms are automatically defined in the covenants.

[10] An exception is provided in [Chodorow-Reich and Falato, 2022], during the Great Financial Crisis (GFC), where some lender demanded immediate repayment of the debt.

reinforce the notion that firms do not want to cross the limits set by the covenants, likely because it is costly to them.

We group the different types of covenants into 3 main categories: *Interest coverage (IC)*, *Debt-to-earnings (DE)*, and *Leverage (LEV)*:

1. *Interest coverage (IC)* covenants define an upper bound/limit on the ratio of interest payments to a measure of firm earnings, for example, EBITDA (Earnings Before Interest, Taxes, Depreciation and Amortization). They can also be expressed in the reverse terms, that is, setting a lower bound/limit on the ratio between earnings and interest payments. Alternative designations of this type of coverage include fixed charge coverage, debt service coverage, or cash interest coverage (which only diverges in small aspects on how the ratio is calculated). In our sample, the loans with the following covenants are included here: *Minimum Interest Coverage*, *Minimum Fixed Charge Coverage*, *Minimum Cash Interest Coverage*, and *Minimum Debt Service Coverage*.

2. *Debt-to-earnings (DE)* covenants set an upper bound/limit to the stock of firm debt compared to earnings (like EBITDA). Crucially, unlike interest coverage covenants, debt-to-earnings covenants do not directly depend on the interest rate. In our sample, the loans with the following covenants are included here: *Maximum Debt to EBITDA*, and *Maximum Senior Debt to EBITDA*.

3. *Leverage (LEV)* covenants set an upper bound/limit on the amount of firm debt, in terms of the firm's assets. Alternative designations of this type of coverage include limits on the Current Ratio, Quick Ratio, Debt to Equity Ratio, Equity to Asset Ratio, and Debt to Tangible Net Worth Ratio. Contrary to some economic models, book values, instead of market values, are used as measures in these covenants. This prevents feedback through the market price of capital or the market value of equity. In our sample, the loans with the following covenants are included here: *Minimum Current Ratio*, *Minimum Quick Ratio*, *Maximum Leverage Ratio*, *Maximum Debt to Tangible Net Worth*, *Maximum Debt to Equity*, *Maximum Senior Leverage*.

3.2.4 Dataset - CRSP/Compustat and Firm Data

We also retrieve additional firm level variables from the CRSP/Compustat Fundamentals Annual Files. In order to match the additional information to our already existing dataset, we use the Gvkey variable (as it is also done by [Chava and Roberts, 2008]). For variable construction, we follow [Görtz et al., 2021]:

- Fixed investment is given by the Capital Expenditures (CAPX) variable. Net investment is CAPX minus Sale of Property, Plant and Equipment (SPPE).

- The capital stock is the net value of Total Property, Plant and Equipment (PPENT).
- Total Inventories (INVT) is end of period total inventories, which are measured in LIFO terms. Inventory investment is defined as the difference between beginning and end of period inventories.
- Net total sales is Total Sales (SALE).
- For cash holdings, the Cash and Short-Term Investments (CHE) variable is used.
- EBITDA is defined by Operating Income before Depreciation (OIBDP).
- Total debt (DEBT) is equal to Long Term Debt Total (DLTT) plus Debt in Current Liabilities (DLC) (which we use for short term debt). Book equity (BE) is given by Stockholder's Equity (SEQ), as described by [Covas and Den Haan, 2011]. We constrain the sample such that book equity (BE) is larger than zero, such that the ratio of debt over assets is bound between zero and one.
- Tobin's Q is calculated as (AT+(PRCC·CSHO)-CEQ)/AT, where AT is Total Assets, CEQ is common equity, PRCC is the Annual Price Close (fiscal year end), and CSHO is Common Shares Outstanding.
- Market Value (MVAL) is the product of Annual Price Close (PRCC, fiscal year end), and Common Shares Outstanding (CSHO).
- Market leverage (MLEV) is calculated according to [Denis and McKeon, 2012], as the ratio between total debt and the sum of total debt and market value (DEBT/(DEBT+MVAL)).
- (External) equity issuance is established as in [Salomao and Begenau, 2019] as subtracting cash dividends (DV) and equity repurchases (PRSTKC) from equity issuance (SSTK).
- Cash flows are calculated by summing Income Before Extraordinary Items (IB) and Depreciation and Amortization (DP).
- Capital reallocation is calculated as the sum of acquisitions (ACQ) and Sales in Property, Plant and Equipments (SPPE). To maximise coverage, we treat missing observations for ACQ as zeros.
- R&D expenditures are given by the Research and Development Expense, XRD.
- Total Liabilities are given by the variable LT.
- Dividend payments are given by Dividends Total, DVT.

- For the TFP (Total Productivity Factor), we apply 3 different estimation methods. The first methodology is based on [Olley and Pakes, 1996], which is widely used in the literature (see, for example, [İmrohoroğlu and Tüzel, 2014]). The main variables that are used for the estimation include the beginning of period capital stock (PPENT), the stock of labor (EMP) and value added. To this, we add the average age of the capital stock, which consists of the ratio between Accumulated Depreciation, Depletion and Amortization (DPACT) and current Depreciation and Amortization (DP). We further smooth this variable for age by taking a 3-year moving average. In the case where a firm does not have information for, at least, 3 years, the average is taken over the available years. All the variables are available at CRSP/Compustat, with the exception of value added, which is calculated as the difference between sales and materials. Sales (SALE) is also directly available in CRSP/Compustat, and materials is calculated as total expenses minus labour expenses. Total expenses is sales (SALE) minus the sum of Operating Income after Depreciation (OIADP) and Depreciation (DP). Data on labor expenses is calculated as the product between employees (EMP) and Staff Expenses (XLR). In addition, we consider 2 alternative methods for the estimation, based on the Ackerberg-Caves-Frazer estimation techniques (see [Ackerberg et al., 2015] for more detail). Using their methodology, we are able to obtain estimates for the Olley-Pakes TFP estimator, as well as for the Ackerberg-Caves-Frazer (ACF) TFP estimator. Although there are some differences in the estimated TFP values across the different methodologies, our results seem to be consistent across the different estimated TFP.

3.2.5 Final dataset - Sample selection

We restrict the sample following the paper of [Greenwald, 2019]. More specifically, we restrict the sample to dates between the first quarter of 1997 and the last quarter of 2007. The initial period is to guarantee that the data from DealScan has enough data on covenants throughout the sample. The last period is chosen to exclude the financial crisis. This is due to a significant change in the enforcement of covenant violations in this period, which can have a significant impact in the analysis of the different variables[11]. This also avoids the zero lower bound period, with small changes of the interest rate, and low transmission mechanisms through the interest rate. Another restriction is applied to the industry sectors considered, as in [Chaney et al., 2012], eliminating firms in mining and building construction (SIC codes 10, 12, 13, 14, 16, 17), public utilities (SIC code 49), and financial, insurance, and real estate (SIC codes 60-67). We also drop firms working in the public administration sector (SIC codes 91-98), firms that cannot be

[11] Nevertheless, we have also considered a less restrictive sample, as in [Drechsel, 2023], and the restrictive sample results seem relatively similar. Very briefly, the author excludes financial corporations (excluding SIC codes 6000-6999), and debt non-denominated in US dollars. The periods considered are the first quarter of 1994 until the last quarter of 2017. But we keep with the analysis of the original sample, given that we also follow the covenant distinction of said paper.

classified (SIC code 99) and firms with missing SIC codes[12].

We also apply additional sample selection procedures, as in [Görtz et al., 2021]:

- We remove the observations if, for any specific firm, there is no information on any of the following variables: CAPX (Capital Expenditures), SALE (total sales), PPENT (net value of Total Property, Plant and Equipment), CHE (Cash and Short-Term Investments), INVT (total inventories) and AT (total assets).

- We also eliminate any firms that never hold or invest in inventories.

- Even though the sample consists of US firms, we delete firms that reported earnings in a currency other than USD.

- We also consider the effects of mergers and acquisitions by dropping firm-year observations if: 1 - there is an acquisition (ACQ) exceeding 15% of total assets (AT); or 2 - if the absolute difference between CAPX and CAPXV (Capital Expenditures on Property, Plant and Equipment) over PPENT exceeds 0.5 and is accompanied by a substantial increase (> 20%) of the absolute growth rate of PPENT.

We start with a general analysis of our sample, presented in Table 3.2. We have the number of observations, as well as the share compared to total observations, and the distinction between private and public firms (as well as those for which information is not provided). In the columns, we have divided by the different type of covenants in our sample. Notice, however, that 1 loan can have different types of covenants. In the first 4 columns (1-4), we differentiate between the loans that do not have any covenant (or the information for the covenants is missing), and the loans that have, at least, 1 covenant of the specified three groups we defined before, the Interest Coverage (IC), Debt-to-EBITDA (DE),and Leverage (LEV) covenants. The next 4 columns (4-8), we have the loans with more than 1 type of covenant, with the 3 possibilities for the combination of each 2 types of covenants, as well as the last option, with loans that contain the 3 different types of covenants. The following 3 columns (9-11) present the observations for loans with only one type of covenant. The last column shows the total within each section.

[12] Even though the sectors not considered in the sample are the same, the motivations are different. In [Chaney et al., 2012], they are not considered due to some being extremely sensitive to real estate or land prices, like the mining and building construction, for example. In our case, again, we follow [Greenwald, 2019], who found that these firms have unusual and volatile rates of covenant incidence, and covenant ratio limits.

Table 3.2: Data description: Observations

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Total						
Observations	111,616	79,991	14,215	30,534	10,537	17,929	502	380	51,905	3,556	12,483	207,768
Share	53.72%	38.50%	6.84%	14.70%	5.07%	8.63%	0.24%	0.18%	24.98%	1.71%	6.01%	100%
						Public						
Observations	71,326	50,443	7,908	20,394	6,514	11,324	426	304	32,909	1,272	8,948	132,111
Share	53.99%	38.18%	5.99%	15.44%	4.93%	8.57%	0.32%	0.23%	24.91%	0.96%	6.77%	100%
						Private						
Observations	36,176	26,173	5,913	8,206	3,829	5,421	76	76	16,999	2,084	2,785	67,218
Share	53.82%	38.94%	8.80%	12.21%	5.70%	8.06%	0.11%	0.11%	25.29%	3.10%	4.14%	100%
						NA						
Observations	4,114	3,375	394	1,934	194	1,184	0	0	1,997	200	750	8,439
Share	48.75%	39.99%	4.67%	22.92%	2.30%	14.03%	0.00%	0.00%	23.66%	2.37%	8.89%	100%

Notes: In this table, we provide the total number of observations from our sample. We additionally subdivide into Public and Private firms (as well as those for which information is not provided). In the columns, we have the distinction between the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is either not available, or there are no covenants associated with the loan).

Notice that there is an overlap across the different columns. For example, column 2 corresponds to the loans that have an IC (Interest Coverage) covenant, which includes columns 5,6, and 9, and excludes column 8 (that is, the loans with both an IC and DE covenants, the loans with both IC and LEV covenants, and the loans with only the IC covenants. We need to exclude the loans with all 3 types of covenants, since they are double counted when we sum columns 5 and 6). Therefore, the total number of observations will be summing column 1 with columns 9-11, then add columns 5-7, and subtract column 8 for two times (since they are counted 3 times when adding columns 5-7).

In terms of both the number of observations, and the distribution across the different covenants, they seem to match to those of [Greenwald, 2019], albeit with some differences (see Table 1 in the paper)[13]. In both cases, the majority of the observations are for loans without covenants (around 50%), and within the covenant cases, most observations are from IC covenants. The main difference would be a higher prevalence of overall observations from the IC covenants (mostly from the IC only covenants), and lower for DE covenants (combined with other covenants). In terms of ownership, most of the observations in our sample are from public listed firms (around 64%), with private (nonpublicly listed) firms consisting of a significant proportion of the remaining amount (around 33%), with only a firm small amount of observations not being identified (around 3%). This is consistent with what we discussed previously, that the information in CRSP/Compustat is mainly from publicly listed companies. But overall, our sample still contains a significant proportion of private firms, as well as loans with different combinations of covenants.

3.2.6 Final dataset - Summary statistics and Firm characteristics

It is likely that the assignment of covenants to firms is not completely random. Thus, it is relevant to provide an initial analysis on the potential differences between firms with and without each type of covenants. In this subsection, we analyze a range of different variables, which suggest that there are differences between firm with and without covenants, as well as between firms with different covenants. Although the differences between the IC and DE covenants seem to be smaller, the differences between the IC and LEV seem to be more pronounced.

We start with some cleaning procedures, also in [Görtz et al., 2021]:

- We change the values of the following variables to missing when they are negative: CAPX, INVT, DVT, CHE, PRSTKC, DP, SPPE, DLTT, DLC, XRD, ACQ, SSTK, PRSTKC, DV.
- The following variables are changed to missing when below or equal to zero: : PPENT (net value of Total Property, Plant and Equipment), PPEGT (gross value of Total Property, Plant and Equipment), SALE, EMP, AT, MVAL, Q.

[13] We conclude that the small differences are the result of the different methodologies used for the matching, since [Greenwald, 2019] resort to the [Chava and Roberts, 2008] dataset for the matching.

- We constrain the sample for very high values of the investment rate, by comparing CAPX and PPENT (that is, high values of CAPX would have to imply high changes in PPENT. Otherwise, that would point to miscoding of investment, CAPX). In the top percentile of CAPX/PPENT, the values of PPEGT, PPENT and CAPX are sent to missing unless the absolute difference between (CAPX-SPPE-ACQ)/PPEGT and the growth rate of PPENT does not exceed 0.1, or if CAPX/PPENT exceeds 5 or CAPX/PPEGT exceeds 2. In the case of CAPX, observations are also changed to missing when CAPX/PPENT exceeds 5 and CAPX/PPEGT exceeds 2 to exclude effects of mergers and acquisitions.

- If the absolute difference between (CAPX-SPPE-ACQ)/PPEGT and the growth rate of PPENT is higher than 0.1, the SPPE values in the top percentile of SPPE/PPEGT are changed to missing values. This is also the case if the SPPE/PPEGT ratio is higher than 0.9.

- For BE (Book Equity), they are set to missing for negative values, or when ratio of BE/AT > 1.

- We winsorize (limit extreme values, similar to what we did for maturity mismatch in the 1st chapter) for the inventory/sales ratio and the disinvestment rate (SPPE/PPENT) at the bottom and top 1 percentile, as well as for Tobin's Q for the bottom and top 0.5 percentile.

- Values for EMP, SALE, PPENT (AT, INVT, CAPX) are replaced with missing in the bottom 0.5 (1) percentile of their respective growth rates. For the top 0.5 (0.01) [1] percentile of the growth rates, this is also applied for EMP, INVT, SALE, AT (PPENT) [CAPX].

- We also apply winsorization for the top and bottom 0.1 (1) percentiles of EBITDA over AT (leverage, external equity issuance over lagged assets, external equity issuance, average age of capital which is DPACT over DP).

- For the depreciation rate (CHE over lagged assets and debt over lagged assets) [the growth rate of cash], the values in the top 0.1 (0.5) [1] percentile are set to missing as well.

- The values of the top 0.5 (1) percentile of the growth rate of DEBT (XRD) (as well as the actual observations).

- We winsorize for the top and bottom 1 percentiles of cash flows, as well as cash flow over contemporaneous (and lagged) total assets. We also set to missing when the CEQ or SEQ raw variables displayed negative values.

- For the top 0.25 percentile of the DVT/AT ratio (as well as DVT over lagged total assets), and the top 0.5 percentile of DVT/SQ, we change the values to missing.

- Finally, we winsorize for the top and bottom 0.1 percentile of the TFP growth rate (in these cases, the TFP values are also set to missing).

We provide the additional statistics in the appendix. We consider similar variables as in Table 1 of [Greenwald, 2019], but while they just provide the median of the different variables, we also show additional elements, including the 25% and 75% quantiles, the mean, standard deviation, skewness and kurtosis. Overall, our median values match with those of [Greenwald, 2019], albeit being a bit higher in our sample. This is likely due to some outliers still remaining in the sample, as can be seen from the kurtosis values.

The first variable is Total Sales, in Table 3.7. As we can see, the amount of sales is lower for the firms without covenants (although higher from the 75% quantile, which would point to result from some outliers in the top part of the distribution, given the levels of the kurtosis and standard deviations). In order to properly compare across different covenants, we should focus the analysis on the last columns, where we have covenants of only each of the three groups. Since the other columns are either of loans that have more than one type of covenant, or group loans that just have one type of covenant with those that have more than 1 type of covenant, we cannot properly isolate the impact of different covenants in those cases, since it is very likely that the effects would be mixed. Although this would exclude some of the loans from the analysis, we still contain a significant portion within the analysis, as we can see from Table 3.2. If we take a look at columns (9-11), we can see that the volume of sales is lower for the firms with IC covenants, and higher for the firms with the LEV covenants (with the firms with DE covenants in the middle).

Next, we consider the analysis of Debt/Assets (where total debt is simply the sum of short-term debt (DLC) and long-term debt (DLTT), and total assets is given by AT), in Table 3.8. In this case, it seems that the firms without covenants have lower Debt/Assets values, although they seem pretty close to the values of LEV covenant firms. Indeed, the firms with LEV covenants have lower values for Debt/Assets compared with firms with DE or IC covenants. Although the values are higher for firms with DE covenants for the lower end of the distribution, they are higher for firms with the IC covenant for the higher end of the distribution.

We also consider the impact of covenants of Debt/BITDA in Table 3.9. Again, the values seem to be lower for the firms with no covenants, although this is reversed for the higher end of the distribution (likely due to some outliers, as it can be seen from the kurtosis values). The values also seem to be higher for the firms with IC covenants than the firms with LEV covenants (matching the findings of the Debt/Assets values). When we compare with the EBITDA/Assets in Table 3.10, there does not seem to be a significant difference between firms with and without covenants, as well as across different covenants. Overall, the results in the last 3 Tables would point to higher levels of debt when loans have covenants, compared to EBITDA and Assets values. This is expected, since lenders are likely to demand more assurances when debt values are higher, compared to assets and EBITDA. Nevertheless, the increase in debt values is higher for firms with IC covenants, than firms with LEV covenants.

But in order to infer on the differences in more detail, we move to the analysis of absolute changes, and not just relative changes. In Table 3.11, we provide the values for the log of assets. In here, we can see that the log of assets is higher for firms with covenants, especially with LEV or DE covenants, when compared to firms with no covenants. In combination with the findings in the previous 3 Tables, this would imply that, for firms with LEV covenants, there is a higher accumulation of assets, EBITDA, and debt. This increase is overall consistent, such that there is no change in the ratios of these variables, between firms with LEV or without covenants. On the other hand, for firms with IC covenants, even though there is accumulation of assets and EBITDA (with possible exception of the higher tails of the distribution), the accumulation of debt is higher, such that the ratios of Debt/Assets and Debt/EBITDA increase for firms with IC covenants, compared with firms with no covenants or just LEV covenants.

For more detail on the debt that is raised by each covenant type, we divide between short-term and long-term debt. The estimations can be seen in Tables 3.12 and 3.13. Starting with short term debt, we can see that the value for firms with LEV covenants is much higher than all the other options. For the DE covenants, they also seem a bit higher than for firms without covenants, while for IC covenants, they seem to be close to the firms without any covenants. For long-term debt, the previous interpretations maintain, with one difference: it seems that the debt levels for firms with IC covenants are higher than those without covenants, especially, for lower bounds of the distribution. Thus, we are able to say that the increase in debt for firms with only LEV covenants is both for short-term and long-term debt, while the increase in the debt for firms with only IC covenants seems to be consisting of long-term debt at the lower end of the distribution.

Additionally, we consider potential differences for the main inputs used for production, the log of employment and the log of capital, in Tables 3.14 and 3.15, respectively. Starting with employment, we can see a clear difference between the firms without covenants and the firms with any covenants. Employment levels are lower for firms without covenants, compared to firms with any covenants, across the different quantiles, and, especially, in the lower quantile. There is also heterogeneity across the different covenants, where firms with the LEV covenants having higher levels of employment, and firms with IC covenants having lower levels (firms with DE covenants are in the middle). The same reasoning applies for capital. Thus, we can conclude that firms with covenants, especially LEV covenants, accumulate a higher amount of inputs.

The last remaining variables we consider for our analysis include the investment rate, the log of TFP (Total Factor Productivity), and Tobin's Q, in Tables 3.16, 3.17, and 3.18, respectively. In terms of the investment rate, the values overall seem to be similar across the different options, with one exception, the firms with the LEV covenants. It seems that the investment rates for firms with LEV covenants yield a lower investment rate, compared to all the other cases. For TFP, the firms without covenants and with IC covenants have similar values, while firms with the DE and LEV covenants are associated with higher TFP values, especially for the lower bounds of the distribution (lower percentiles). For Tobin's Q, the values are close between the firms with DE covenants and without covenants. For firms with LEV covenants, the values are lower, especially for the higher bounds of the distribution. The firms with IC covenants are associated with higher levels of Tobin's Q, although the difference is relatively small (considering the variable is expressed in levels and not in logs).

In general, our results match those pointed out by [Greenwald, 2019]. First, firms with covenants have higher values for sales, as in our sample. They also find that firms with covenants have a higher size of their balance sheet. Although this seems to verify for the firms with LEV covenants, this does not seem to be the case for the firms with IC covenants. In our sample, both the amount of debt and assets is higher for firms with LEV covenants, but the assets for firms with IC covenants seem similar to firms without covenants. Finally, the authors point to higher values of debt for the firms with covenants, a similar result to the one we find in our sample.

3.2.7 Final dataset - Robustness to size and age

In the last subsection, we considered a general analysis into the potential differences between firms with and without covenants, as well as differences across covenants, for different variables. Overall, our findings point to higher accumulation of resources and debt for firms with covenants than firms without covenants, especially for firms with LEV covenants. However, firms with IC covenants accumulate more debt than assets, reflecting an impact on their ratios, unlike LEV covenant cases. They also show that firms with covenants accumulate more long-term debt compared to firms without covenants. For short-term debt, firms with LEV covenants accumulate more debt than all the other options, while firms with IC covenants seem to have similar levels to firms without covenants. In terms of Tobin's Q, we find that firms with LEV covenants are associated with lower levels of Tobin's Q, and firms with IC covenants are associated with higher Tobin's Q. Finally, we also found that TFP values are higher for firms with LEV and DE covenants than for firms with IC or without covenants.

In this subsection, we seek to infer on the possibility that these differences are caused by elements other than the covenants themselves, for example, due to their size or their age. Thus, we divide our sample into 2 subsets, according to either size or age, and confirm whether these differences maintain, or if they are simply a reflection of the size or age difference between the firms. In terms of their size, we divide the sample into 2 groups, according to the median of the log of assets. The subset of firms below the median will consist of the small firms sample, and the subset of firms above the median will consist of the large firms sample.

We begin with the analysis of the assets, in Table 3.19. As expected, large firms accumulate more assets than small firms. But as we can see, when we separate the sample between small and large firms, the higher accumulation of resources from firms with LEV covenants only seems to hold for the subset of large firms (while for firms with IC covenants, seems to be close, or lower, than firms without covenants, within this subset). If we evaluate the subset of small firms, we can see that the relationship is reversed. Firms with LEV covenants have fewer assets than firms without covenants, and firms with either IC or DE covenants have more assets than either of the previous 2 groups. Thus, we can conclude that the resource accumulation that we have identified previously for the firms with LEV covenants is due to their size in the sample, and not due to the potential differences stemming from the covenants themselves. We also consider that this is likely the case for other similar variables (including EBITDA, sales, and others).

We follow with the analysis for short-term debt, as well as long-term debt, displayed in Tables 3.20 and 3.21, respectively. For short-term debt, even though we can clearly see a difference between the amounts for small firms and large firms (as expected, since small firms are likely to contract less short-term debt than large firms), the relationship is consistent across different covenants, as well as with our previous results. That is, that short-term debt is higher for firms with LEV covenants than firms with IC covenants, or firms without covenants (the only exception being the lower quantile for the small firms). It also seems that, as before the values for firms with IC covenants follow closely to the firms without covenants (although they are higher when comparing small firms, and lower when comparing large firms). For long-term debt, however, we can see that the log of long-term debt is only higher for firms with LEV covenants in the subset of large firms, and this does not hold for the subset of small firms. In fact, long-term debt for small firms with LEV covenants is the lowest, compared with all the other options in the small firm subset. Thus, the higher levels of long-term debt for firms with LEV covenants that we found previously is due to the size of firms, and not due to the LEV covenants. Finally, as expected, large firms accumulate more short-term and long-term debt than small firms.

We also evaluate the differences in the values of Tobin's Q, as in Table 3.22. In terms of difference between small and large firms, there is no consistent difference, although small firms seem to have a higher Tobin's Q than large firms, in general. Nevertheless, the previous relationship identified maintains across covenants, for each of the 2 subsets. That is, the Tobin's Q is higher for firms with IC covenants and lower for firm with LEV covenants, whether firms are large or small. It would imply that the results for the Tobin's Q are not driven by the size of the firms.

The remaining variable that we also need to test for potential differences related to firm size is the TFP, with the results presented in Table 3.23. As expected, larger firms have higher levels of TFP, when compared to smaller firms, for all the different possible covenant combinations. This is likely related to economies of scale gains in productivity. It also seems that the previous differences maintain, with the firms of LEV covenants achieving a higher log of TFP, when compared with the firms with IC covenants, as well as the firms without covenants (the only exception is the 75 percentile for large firms). Thus, the difference for the log of TFP across firms with different covenants is not due to their size.

Next, we consider the possibility that the previous differences identified are due to the age of the firms, rather than their covenants. For the age of the firms, we consider the IPO (Initial

Public Offering) variable in order to make the distinction. As before, we calculate the median, and separate into 2 subsamples. The firms that have an IPO before the median are considered the old firms, and those with an IPO after the median are considered the new firms. Given our previous results, we will focus the analysis on the 2 variables that showed a difference across different covenants, and which difference cannot be attributed to the size of the firm[14]. Thus, we consider potential differences in the TFP and the short-term debt, presented in Tables 3.24 and 3.25, respectively.

Starting with TFP, in almost all cases, younger/newer firms have higher values for log of TFP than older firms. This is expected, since younger firms are likely to employ more recent technology, more efficient production processes, or face higher competition than older firms, they are likely to be more productive. Also, we can see that the TFP for firms with LEV covenants are higher than firms with IC covenants, for all scenarios. This is also the case when we compare with firms without covenants, instead of firms with IC covenants (with a few exceptions for the younger firms, but still holds on average for this subset). Thus, the previous results we found for TFP are also not driven by the difference in the age of the firms, and are robust to this characteristic.

Moving to the short-term debt, younger firms seem to have more accumulated debt than older firms. One possible explanation is that older firms have more information on their performance over the years that can be provided to lenders, and have an easier time contracting long-term debt, instead of short-term debt. On the other hand, younger firms have fewer information to provide, and will have to rely more on short-term debt, since lenders would be taking a higher risk with long-term debt. When comparing across covenants, our previous conclusions maintain in both subsamples, which is that firms with LEV covenants have higher levels of short-term debt, when compared to all the other options. Thus, this higher level of short-term debt for firms with LEV covenants cannot be attributed to differences on the age of the different firms.

Lastly, even though there was just a feeble difference between the Tobin's Q in the total sample (where firms with LEV covenants have a lower Tobin's Q than firms with IC covenants), we test for robustness to the age of the firms. Overall, it seems that older firms have a lower Tobin's Q than younger firms (albeit a few exceptions, which can be seen for the firms with DE covenants), and almost all have a value above 1. This would imply that the total market value of the firms is above their total asset value, and the difference is higher for younger firms. This could either reflect issues with overvaluation of younger firms (which could be due to having fewer years of activity and information, and would require more time for the market value to

[14] We also conducted the analysis for the long-term debt, as well as assets. Here, given the previous results, we provide just a short summary: For older firms, long-term debt is higher for LEV firms than for IC firms (for percentiles lower than 25%, this is reversed). For new firms, LEV firms have higher long-term debt than IC firms for almost all cases (except at 99% and lower than 10%). For the assets, for older firms, the LEV firms have more assets than IC firms (except for lower than 25% percentile). For new firms, LEV firms have more assets than IC firms (except for lower than 5% percentile). Even though the results seem robust to the different ages of the firms, as we saw previously, they seem to be driven by the size of the firm, and not the different covenants.

reflect the true value of the firm), or that younger firms can be seen as more dynamic, and have higher expectations for future economic growth than older firms. The previous relationship across covenants that we previously identified still maintains. The firms with LEV covenants have lower values, while firms with IC covenants have higher values for Tobin's Q. Thus, the differences across covenants for this variable that we have previously identified are not due to an age difference between firms.

Summing up, in this subsection, we tested for the possibility that the previously identified differences were either driven by differences in the firms' age or size (or both), and not due to differences associated to the covenants. We found that, for the case of assets and long-term debt, the difference is explained by the size of the firm, instead of the different covenants. However, for the log of TFP, the short-term debt, and the Tobin's Q, the differences remain after accounting for size or age of the firms.

3.2.8 Final dataset - Regression estimation and Motivation

In this final subsection, we attempt to infer on the possibility of a relationship between the variables that we previously identified as having a difference across covenants. More specifically, we will regress the log of TFP on either the Tobin's Q or the log of short-term debt, and add dummies to interact with each of the 3 covenant groups[15]. If the impact is statistically significant for any of the interaction terms, and if it is different across covenants, we also test by adding additional controls, which simply consist of some of the variables described in subsection 3.2.4. It is important to note that the regression in this subsection is robust to the use of each of the 3 different methodologies for the estimation of TFP, as well as both sample selection datasets (described in the beginning of subsection 3.2.5). Thus, the estimation procedure will be as follows:

$$ln(TFP_{it}) = \alpha_i + \beta_X X_{it} + \beta_{IC} X_{it} * IC + \beta_{DE} X_{it} * DE + \beta_{LEV} X_{it} * LEV + G_{it}'\Gamma + \varepsilon_{it} \tag{3.1}$$

where the right-hand side of the equation consists of our dependent variable, the log of Total Factor Productivity (TFP), and the left hand side include our main independent variable, X_{it} (which, for the results that we will present here, is either Tobin's Q or the log of short-term debt (ln(dlc)), but, as we explained before, we also estimated using additional covariates, including the investment rate), the interaction between the main independent variable and each of the 3 covenants, and the additional control variables, as represented by G_{it}. All the estimated

[15]We have also regressed the log of TFP on additional variables, considering the interaction with the different covenants as well, including the long-term debt, total assets, investment rate, and others. It would be possible that, even though there were no difference on these variables across covenants, that they would exert a difference across them on the TFP impact. We have not included the results here since they either were not statistically significant, or lost significance when some of the controls were introduced.

regressions include fixed effects and robust standard errors.

The controls include variables previously described in subsection 3.2.4, including: log of long-term debt (ln(dltt)), the investment rate (invr), log of total assets (ln(at)), ratio of EBITDA over total assets (EBITDA/at), ratio of debt over EBITDA (debt/EBITDA), ratio of debt over total assets (debt/at), log of book equity (ln(seq)), log of net total sales (ln(sale)), log of Cash and Short-Term Investments (ln(che)), log of total liabilities (ln(lt)), market leverage (mlev), log of capital re-allocation (ln(cr)), log of total inventories (ln(invt)), log of external equity issuance (ln(esstk)), and log of R&D expenditures (ln(xrd)).

We begin with the regression on Tobin's Q, where the results can be seen in Table 3.3. As we can see, there is a consistent positive correlation between the Tobin's Q and the log of TFP. This is expected, as a higher Tobin's Q implies higher firm valuation, and it is likely that firms with higher productivity are also those with higher valuation. In terms of the interaction with the 3 main groups of covenants, there is no consistency, in term of statistical significance, across the different scenarios. The most consistent would the interaction with the IC covenants. However, when introducing both short-term debt and long-term debt, in column (3), or when introducing the log of external equity issuance (ln(esstk)), and log of R&D expenditures (ln(xrd)), in column (8), we can see that the interaction term loses its statistical significance. Thus, we can argue that the type of covenants associated with the loan or with the firm does not seem to have an impact on the correlation between the Tobin's Q and the log of TFP.

Table 3.3: Total Factor Productivity and Tobin's Q

	Dependent variable: $ln(TFP_{it})$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Q_{it}	0.0868**	0.0803**	0.1312**	-0.0332^{+}	0.0790**	0.1140**	0.1079**	0.0724**
	(0.0220)	(0.0227)	(0.0171)	(0.0190)	(0.0226)	(0.0113)	(0.0123)	(0.0166)
$Q_{it} * IC$		0.0921**	0.0607	0.0563*	0.0883**	0.0684**	0.0626*	0.0393
		(0.0319)	(0.0396)	(0.0242)	(0.0322)	(0.0223)	(0.0263)	(0.0404)
$Q_{it} * DE$		0.0849*	0.0347	-0.1317	0.0715	0.0194	0.0228	-0.1043
		(0.0431)	(0.0577)	(0.1521)	(0.0490)	(0.0218)	(0.0264)	(0.2604)
$Q_{it} * LEV$		0.0174	-0.0008	0.0468^{+}	0.0164	-0.0121	-0.0093	-0.0167
		(0.0354)	(0.0566)	(0.0246)	(0.0347)	(0.0286)	(0.0305)	(0.0411)
$ln(dltt_{it})$			0.0188**					
			(0.0069)					
$ln(dlc_{it})$			-0.0112*					
			(0.0055)					
$ln(at)_{it}$				0.2287**				
				(0.0113)				
$(EBITDA/at)_{it}$				6.6269**				
				(0.1996)				
$(debt/EBITDA)_{it}$					-0.0013			
					(0.0009)			
$(debt/at)_{it}$					-0.4609**			
					(0.0851)			
$ln(seq)_{it}$						0.0133		
						(0.0198)		
$ln(sale)_{it}$						0.1529**		
						(0.0258)		
$ln(che)_{it}$						0.0499**		
						(0.0073)		
$mlev_{it}$							-0.9683**	
							(0.0631)	
$ln(invt)_{it}$							0.1092**	
							(0.0141)	
$ln(esstk)_{it}$								0.0490**
								(0.0087)
$ln(xrd)_{it}$								0.0404^{+}
								(0.0234)
Fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.0402	0.0429	0.0544	0.4989	0.0610	0.1226	0.1286	0.0636
F-statistic	15.58	25.41	18.10	255.96	23.57	78.06	106.08	15.77
Observations	207,415	207,415	176,171	207,415	206,809	196,957	168,883	23,002

Notes: This table presents results from estimating log of Total Factor Productivity on Tobin's Q, the interaction between Tobin's Q and each of the 3 covenants, and the additional control variables. The additional controls at this table are as follows: log of long-term debt (ln(dltt)), log of short-term debt (ln(dlc)), log of total assets (ln(at)), ratio of EBITDA over total assets (EBITDA/at), ratio of debt over EBITDA (debt/EBITDA), ratio of debt over total assets (debt/at), log of book equity (ln(seq)), log of net total sales (ln(sale)), log of Cash and Short-Term Investments (ln(che)), market leverage (mlev), log of total inventories (ln(invt)), log of external equity issuance (ln(esstk)), and log of R&D expenditures (ln(xrd)). Reported R^2 values are from within variation. Standard errors in parentheses are robust. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

We, then, shift to the analysis of the correlation between the log of TFP and log of short-term debt, in Table 3.4. As we can see, there is no consistency for the statistical significance of the correlation between short-term debt and log of TFP, as identified in the initial scenarios, from column (1) to column (3) (although it retains significance for the other columns). On the other hand, the interaction between the short-term debt and the IC covenant seems to be consistent across the different scenarios. This would imply that firms with IC covenants have an additional negative correlation between short-term debt and log of TFP, which does not verify for firms with either DE or LEV covenants. This is consistent with our findings so far. Recall that we identified that firms with IC covenants have lower levels of TFP, as well as short-term debt, when compared to firms with LEV covenants, and these differences are robust to differences in firms age, size, and other controls. The evidence in this subsection suggests that firms with IC covenants accumulate lower levels of short-term debt, given their negative correlation with productivity. Nevertheless, they still resort to short-term debt and, thus, would have a negative effect on their TFP, resulting in lower levels of productivity, when compared to firms with LEV covenants.

From here, we build the motivation for this chapter. We will consider a theoretical model, with two main types of firms, which are mainly distinguished by their constraints: firms with earnings-based constraints (for which most would fall under the IC covenant category), and firms with asset-based constraints (for which most would fall under the LEV covenant category). In order to support this connection, we rely on the works of [Lian and Ma, 2021] and [Greenwald, 2019]. [Lian and Ma, 2021] combine different data sources, and show that only 20% of credit to US firms is asset-based, while 80% is earnings-based. They also find that earnings-based measures have a strong impact on borrowing and investment, while real estate values have a limited impact. Finally, they state that earnings-based constraints can also avoid fire-sales effects on firms. [Greenwald, 2019] focus on constraints where the interest payments are restricted by earnings, which are often associated with earnings-to-debt restrictions (these would be the Interest Coverage (IC) constraints that we have discussed). They also calculate that they are present in over 80% of firms with covenants. Thus, we consider that there is a significant overlap (or similarity) between the IC covenants and earnings-based constraints.

We will also incorporate the main characteristic in our findings: that short-term debt will have a negative impact on the TFP of firms with earnings-based constraints, which will not be the case for firms with asset-based constraints. We will construct replications for this theoretical model, and assess the how well it fits our actual data.

Table 3.4: Total Factor Productivity and Short-term debt

	Dependent variable: $ln(TFP_{it})$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ln(dlc_{it})$	-0.0043	-0.0087	0.0072	-0.0402**	0.0411**	-0.0430**	-0.0395**	0.0289**
	(0.0059)	(0.0060)	(0.0057)	(0.0058)	(0.0050)	(0.0056)	(0.0060)	(0.0071)
$ln(dlc_{it})*IC$	-0.0424*	-0.0423*	-0.0357*	-0.0335^{+}	-0.0278^{+}	-0.0311^{+}	-0.0383*	-0.0343^{+}
	(0.0177)	(0.0184)	(0.0166)	(0.0177)	(0.0145)	(0.0178)	(0.0180)	(0.0184)
$ln(dlc_{it})*DE$	0.0822	0.0838	0.0925*	0.0478	0.2099*	0.0471	0.0573	0.0063
	(0.0546)	(0.0556)	(0.0403)	(0.0521)	(0.0928)	(0.0509)	(0.0549)	(0.0581)
$ln(dlc_{it})*LEV$	-0.0423	-0.0530	-0.0380	-0.0445	-0.0245	-0.0455	-0.0437	-0.0684
	(0.0391)	(0.0440)	(0.0379)	(0.0378)	(0.0336)	(0.0367)	(0.0386)	(0.0507)
$ln(dltt_{it})$		0.0121^{+}						
		(0.0070)						
$invr_{it}$			0.4564**					
			(0.0545)					
Q_{it}			0.1275**					
			(0.0134)					
$ln(at_{it})$				0.1771**				
				(0.0139)				
$(EBITDA/at)_{it}$					6.4698**			
					(0.0009)			
$(debt/EBITDA)_{it}$					-0.0007			
					(0.0006)			
$(debt/at)_{it}$					-0.3264**			
					(0.0870)			
$ln(seq)_{it}$						-0.0033		
						(0.0221)		
$ln(sale)_{it}$						0.2101**		
						(0.0314)		
$ln(che)_{it}$						0.0369**		
						(0.0076)		
$ln(lt)_{it}$							0.1304**	
							(0.0130)	
$mlev_{it}$								-1.1396**
								(0.0739)
$ln(cr)_{it}$								0.0175**
								(0.0038)
Fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.0024	0.0045	0.0670	0.0467	0.4515	0.0826	0.0289	0.0891
F-statistic	2.99	3.39	35.64	37.50	150.03	34.57	25.11	43.74
Observations	180,886	176,411	180,637	180,886	180,838	170,873	180,847	93,634

Notes: This table presents results from estimating log of Total Factor Productivity on short-term debt (dlc), the interaction between short-term debt and each of the 3 covenants, and the additional control variables. The additional controls at this table are as follows: log of long-term debt (ln(dltt)), the investment rate (invr), the Tobin's Q (Q), log of total assets (ln(at)), ratio of EBITDA over total assets (EBITDA/at), ratio of debt over EBITDA (debt/EBITDA), ratio of debt over total assets (debt/at), log of book equity (ln(seq)), log of net total sales (ln(sale)), log of Cash and Short-Term Investments (ln(che)), log of total liabilities (ln(lt)), market leverage (mlev), log of capital re-allocation (ln(cr)). Reported R^2 values are from within variation. Standard errors in parentheses are robust. +,*,** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

3.3 Literature Review

3.3.1 Borrowing Constraints

Financial frictions play a central role in our model, by constraining the firm's ability to resort to borrowing funds. [Diamond and Dybvig, 1983] are among the first papers to point out the importance of this characteristic, by pointing out the vulnerability of the financial system to bank runs, and it's potential self-fulfilling component. [Gertler and Gilchrist, 2018] provide a summary of the contribution of research incorporating market frictions, how they may generate financial crisis and how it can be transmitted to the real sector. They provide some information on several papers which incorporate the financial accelerator mechanism like we have, but the transmission of the crisis operates through different sectors of the economy. For example, [Mian and Sufi, 2014], [Mian et al., 2013], [Eggertsson and Krugman, 2012], [Justiniano et al., 2010], and [Guerrieri and Lorenzoni, 2017] incorporated balance sheet constraints on households, while [Gertler and Kiyotaki, 2010], [He and Krishnamurthy, 2013], and [Brunnermeier and Sannikov, 2014], incorporate balance sheet constraints on banks. [Gertler and Kiyotaki, 2010] use credit market frictions to evaluate how disruptions in financial intermediation can induce a crisis that affects real activity, and how various credit market interventions by the central bank and the Treasury might work to mitigate the crisis. [Duncan and Nolan, 2017] provide a more extensive review on DSGE models with financial frictions before and after the crisis, as well as some empirical literature as well. The authors claim that the main differences revolve around the extension of the financial accelerator mechanism to new agents, the proper connection to an intermediary/financial sector/agent, as well as the incorporation of non-linear characteristics. The traditional models can be defined in 2 main approaches: 1 - a sticky-price DSGE model with costly state verification (as in [Bernanke and Gertler, 1999] and [Carlstrom and Fuerst, 1997]), 2 - a model with differences in human capital and difficulties in contract enforcement by the lender, as in [Kiyotaki and Moore, 1997]. In both these models, agents are exposed to shocks that affect their ability to accumulate resources and smooth their objective (either consumption, production profitability, or other) overtime. The presence of credit frictions results in an amplification of these shocks (both intertemporally and intratemporally) through a fire-sales effect. Since agents will face borrowing constraints dependent on the value of resources, which are influenced by the shocks, in addition to influencing the accumulation of resources, it will also influence their ability to borrow as well. Other papers have taken this approach to focus on the housing sector, including [Iacoviello, 2005], [Guerrieri and Uhlig, 2016] and [Mian and Sufi, 2016]. Some earlier papers focused on the analysis of these frictions from a partial equilibrium perspective. These include [Minsky, 1986], [Bhattacharya et al., 2004] and [Allan and Gale, 2007]. However, many of the contributions of these papers are captured in more recent general equilibrium models. For example, the credit cycles characteristic in [Minsky, 1986] has also been incorporated in [Boissay et al., 2016] and [Azariadis et al., 2016]. One of the changes made by the more recent literature was to turn to the possibility of the shocks starting in the financial sector. This is the main point argued by [Nolan and Thoenissen, 2009], in which the authors establish that these shocks seem to explain a higher portion of business cycles, as well as variance of GDP, compared to standard TFP, money and monetary shocks; and are highly negatively correlated with the external finance premium. They also argue that these models do not consider defaults, deposit protection, financial regulations, and other central elements in this analysis. [Gilchrist et al., 2009] also incorporate this approach and, using a different empirical methodology, find that credit market shocks provide a large contribution in explaining US business cycles between 1990 and 2008. [Hall, 2010] show that these models are able to capture the initial decline in the economy after a financial crisis, but does not seem to fare well in terms of the dynamic properties. [Christiano et al., 2014] also falls under this category. Other papers have also provided some additional limitations to these traditional models, which mainly stem from the information on the shocks being public and observable by all agents. [Di Tella, 2017] points out that this opens the possibility to define and enforce insurance contracts contingent on these risks. [Carlstrom et al., 2016] apply this strategy to [Bernanke et al., 1999] to show agents can neutralize the financial accelerator effect and achieve better outcomes. [Krishnamurthy, 2003] and [Nikolov, 2014] follow the same reasoning for the [Kiyotaki and Moore, 1997] model. [Gomes et al., 2016] consider a model with equilibrium defaults, in which a temporary decrease in inflation increases default rates, as well as the debt burden on the firms, such that it impacts their ability to take on additional debt, affecting their investment and production decisions. A necessary element in this result is that the expected maturity of the debt needs to be higher than one period. The main differences compared to our model would be in terms of the lasting firm heterogeneity that we are considering, and the destination given to the resources in the case of defaults. In their model, the authors consider that the number of firms is constant (no firms leave or enter the market), but a portion of the firm's capital is destroyed in the restructuring process. Instead, we consider that there is no loss of resources for the aggregate economy (as they are split between the financial intermediary and the households), and we consider that the firms that have defaulted have to leave the market, and will be replaced by new firms. [Stein, 2012] show that lack of constraints on intermediaries can lead to excessive short-term debt and increase costs of financial crises.

More specifically, our model considers whether different types of constraint will have different impacts on limiting the firm's behaviour, and whether they are binding. We follow [Green, 2019] in grouping the different covenants in 3 main groups. In their paper, they find that Interest coverage (IC) covenants lead to higher amplification of interest rate effects in borrowing and investment. They question the relevance of covenants in mitigating the agency costs of debt, and suggest that they are essential to allow tax benefits of debt to offset costs of financial distress. Others also include the impact of potential violation of these constraints as well. [Almeida and Campello, 2007] investigate how pledgeable assets influence borrowing, and find that, if firms are financially constraint, investment-cash flow sensitivities change in the same direction as the tangibility of firms' assets (that is, the more tangible the firms' assets are, the higher the sensitivity of the investment-cash flow). [Almeida et al., 2004] hypothesize that only constrained firms should have a positive sensitivity to cash flows, and find evidence in support of that hypothesis in their sample of manufacturing firms between 1971 and 2000. [Chaney et al., 2012] use the impact of changes in real estate prices as a shock on firm's collateral value, and, then, proceed to infer on the sensitivity of firm's investment resulting from this changes. Through a sample of firms between 1993 and 2007, a representative firm in the US invests 0.06$ out of each 1$ of collateral. [Nini et al., 2009] are also interested in the impact of constraints on firm investment policy, and find that restrictions on firms capital expenditures reduces their investment, but also increases in their market value and operating performance. [Chava and Roberts, 2008] are amongst the first papers to use debt covenants to study how financial frictions impact corporate investment. The main findings include a sharp drop in investment, following a covenant violation, especially, in the presence of agency and information problems, pointing to how state-contingent allocation of control rights can help diminish these investment distortions associated with the covenants. [Chodorow-Reich and Falato, 2022] also consider the effect of covenant violations, focusing on the channel between banks and non-financial firms, and showing that most of the cross-sectional variation in credit supply during the Great Financial Crisis can be attributed to credit reduction to borrowers that did not comply with covenants. [Demerjian and Owens, 2016] attempt to innovate the measure of probability that a borrower will not comply with covenants in private contracts, comparing to previous methodologies. [Diamond et al., 2020] find that firms increase their debt and reduce/maintain their collateral pleadgebility when the market expects higher future liquidity, which prolongs negative effects in a downturn. [Donaldson et al., 2019] evaluate the differences between secured and unsecured debt, in terms seniority of repayment in case f default. They show that, even though this hierarchy leads to conflict between the creditors, it can be optimal. [Murfin, 2012] consider how the strictness of loan contracts offered are affected by lender-specific shocks, especially, the impact of recent defaults on their screening ability. In the previous section, we also discussed resorting to the sample selection applied by [Drechsel, 2023]. They compare earnings-based borrowing constraints with collateral constraints, and find that positive investment shocks have opposite effects depending on the constraints, where firms with earnings-based borrowing constraints increase their borrowing, while firms with collateral constraints decrease their borrowing. This is due to the shock decreasing the value of the collateral, but increasing earnings at the same time. [Dávila and Korinek, 2018] infer on how borrowing constraints affect optimal regulatory policy, and identify two main externalities: distributive externalities that arise from incomplete insurance markets and collateral externalities that arise from price-dependent financial constraints. [Lanteri and Rampini, 2023] also incorporate these 2 externalities in their model, finding the first externality exceeds the second one, and that capital price is inefficiently high in equilibrium. A possible solution is new investment subsidies. [Bianchi, 2016] consider working capital and equity constraints, and attempt to infer on the interaction between moral hazard and possible bailouts. The results reflect that the outcome depends on the scope of bailouts. Mainly, if bailouts are systemic and broad-based, then moral hazard effects are limited: On the other hand, if they are idiosyncratic and targeted, it makes the economy more exposed to financial crisis. [Wolf, 2020] evaluates how pecuniary externalities resulting from wage rigidities independently of financial constraints and demand channels.

The following papers place a higher focus on earnings-based constraints, rather than asset-based constraints. [Bianchi, 2011] focus on the impact of earnings-based constraints on the country's external stance, differentiating between the tradable and non-tradable sector. [Benigno et al., 2013] also consider the effects of constraints in borrowing below optimal levels, but consider a different channel. In their case, this is a result of households having lower wages, constraining their borrowing. In [Schmitt-Grohé and Uribe, 2020] case, higher wages leads households to increase their savings (and reduce borrowing), in order to safeguard against possible future crises. [Fazio, 2021] resort to earnings-based constraints to evaluate the implications of a credit crunch at the zero lower bound (ZLB) on interest rates. Their model generates too many low-productivity firms (zombie firms), which generates a negative spillover effect on the borrowing ability of more productive firms, by inflating labor costs and reducing overall profits. They find that liquidating the zombie firms can improve efficiency, but not when the economy is at the lower bound, since they take advantage of idle resources, boosting GDP and welfare. [Ottonello et al., 2022] consider the timing component of collateral constraints, and show that the impact depends on if current or future prices affect the credit access. [Caglio et al., 2021] show that earnings-based constraints are prevalent for smaller or medium sized firms (SMEs). [di Giovanni et al., 2022] infer on the impact of earnings-based constraints applied to government procurement auctions in Spain on firms outcomes.

In the case of our model, we consider financial frictions resulting from the non-contingent bonds, which introduce the possibility of defaults, even in equilibrium. These types of contracts were first included by [Eaton and Gersovitz, 1981], when considering international lending. [Aguiar and Gopinath, 2006] and [Arellano, 2008] resort to this type of contracts for a quantitative analysis of sovereign debt. [Chatterjee et al., 2007] apply them in the case of unsecured household debt, while [Nakajima and Ríos-Rull, 2005] extended this last framework to include aggregate shocks. [Arellano et al., 2012] combine non-contingent bonds with productivity differences and equilibrium defaults (similar to the characteristics of our model), and find support for aggregate fluctuations resulting from large labor wedges, which are generated by uncertainty shocks at the firm level. Unlike our model, they consider that labor is predetermined, and do not consider capital investment (although they also consider that defaulting firms must exit the economy).

3.3.2 Firm heterogeneity

Similar to other recent papers, the heterogeneity in our model will manifest in the firm sector. [David and Zeke, 2021] also consider a heterogeneous TFP (Total Factor Productivity) shock, and consider the source of the heterogeneity being generated by the resource allocation, and explore the corresponding cyclical dynamics, as well as optimal fiscal and monetary policy. [Ottonello and Winberry, 2020] propose a model in which the source of heterogeneity is instead in the default risk, and find the aggregate effect of monetary policy may depend on the dynamic distribution of default risk. [Angeletos and La'O, 2020] introduce informational frictions, either in terms of private information, or rationally inattentiveness, to generate difference between the firms, while [La'O and Tahbaz-Salehi, 2020] consider different input-output connections. [David and Venkateswaran, 2019] consider potential different source of capital "misallocation", from technological, to informational, and firm specific factors. [Kurtzman and Zeke, 2020] focus on the large-scale asset purchase by the central banks, and the potential misallocation of resources through their heterogeneous effect on firm credit spreads. [Arellano et al., 2016] construct a model with heterogeneous firms, financial frictions, non-contingent debt and equilibrium default, and evaluate the impact of a change in volatility of firm productivity shocks. They find that their model generates most of the decline in output and labor, as well as the tightening of financial conditions, during the Great Recession of 2007–2009. [Veracierto, 2002] take a DSGE model with firm heterogeneity and investment irreversibilities at the establishment level, and test how they affect aggregate responses to productivity shocks. [Caggese, 2007] consider a model with heterogeneous firms, financing constraints and irreversibility constraints. They find that the interaction between these 2 constraints is crucial to explain the volatility and procyclicality of inventories and deliveries of US manufacturing firms. [Gomes and Schmid, 2010] consider firm heterogeneity in terms of their leverage, in a model with endogenous default, to evaluate the impact on credit spreads. [Gilchrist et al., 2014] consider an idiosyncratic component in terms of uncertainty in investment, to differentiate the firms in the model, where the uncertainty works through the credit spreads. [Zetlin-Jones and Shourideh, 2017] consider heterogeneity in the ownership (private vs public) of intermediate goods producers, and how they behave in the face of financial shocks that affect their access to external funds. They conclude that there are some limitations on the capability of financial shocks to generate significant economic fluctuations, and, instead, point to non-financial linkages in understanding the importance of financial shocks.

Although the technology shocks in our paper are exogenous, other papers analyse the effects of endogenous technology shocks, including [Romer, 1990], [Aghion and Howitt, 1992], and others. Some studies focus on the connection between these shocks and human capital (e.g., [Chari and Hopenhayn, 1991], [Caselli, 1999], [Manuelli and Seshadri, 2003]). Other papers also incorporate uncertainty, and a learning process of these shocks for the agents subject to them , including [Jovanovic, 1982], [Jovanovic and Nyarko, 1996], and [Atkeson and Kehoe, 2007]. [Mokyr, 1990] argues in his paper that "macroinventions" are the main source of economic growth.

To support our framework, we also find extensive literature supporting firm heterogeneity, as well as changes in productivity between different firms and different periods. [Bloom, 2009] documents that various cross-sectional dispersion measures for firms in panel datasets are countercyclical; [De Veirman and Levin, 2011] find similar results using the Thomas Worldscope database. [Kehrig, 2011] uses plant-level data to document that the dispersion of total factor productivity in US durable manufacturing is greater in recessions than in booms. [Vavra, 2011] presents evidence that the cross-sectional variance of price changes at the product level is countercyclical. [Christiano and Ikeda, 2013] present evidence on the counter-cyclicality of the cross-sectional dispersion of equity returns among financial firms. [Alexopoulos and Cohen, 2009] construct an index based on the frequency of time that words like uncertainty appear in the New York Times and find that this index rises in recessions. It is unclear, however, whether the Alexopoulos-Cohen evidence about uncertainty concerns variations in cross-sectional dispersion or changes in the variance of time series aggregates. [Bachmann and Moscarini, 2011] explore the idea that the cross-sectional volatility of price changes may rise in recessions as the endogenous response of the increased fraction of firms contemplating an exit decision. [D'Erasmo and Moscoso-Boedo, 2011] and [Kehrig, 2011] provide two additional examples of the possible endogeneity of cross-sectional volatility. [Chugh, 2016] incorporate cross-sectional volatility of firm productivity in their model, in order to evaluate how the firm fares in reproducing cyclical fluctuations. [Bloom et al., 2012] and [Bachmann and Bayer, 2013] provide microeconomic evidence of the volatility of firm risk (changes in the dispersion of firm cross-sectional distribution) throughout the business cycle, and of it's countercyclicality with respect to GDP. Based on [Pástor and Veronesi, 2009], they focus on the impact of technological shocks in stock prices. They argue that the large uncertainty regarding the productivity of new technologies, and it's time-varying uncertainty can be an alternative explanation to irrational behaviour of agents regarding the observed stock prices, and it's bubble-like patterns when new technology comes into place [16]. Finally, they show that the idiosyncratic risk regarding these shocks can turn into systematic risk, if the technology is adopted on a large scale.

One of the channels of firm heterogeneity that we consider in this model regards different TFP (Total Factor Productivity) shocks. [Cooley and Quadrini, 2001] construct a workhorse model of heterogeneous firms with technological difference, financial market frictions and default risk. [Khan et al., 2017] consider that business cycles are generated by firms' differences in total factor productivities, and financial assets. [Buera et al., 2011] provide a quantitative analysis to evaluate the relationship between aggregate/sector-level total factor productivity (TFP)

[16] "Every previous technological revolution has created a speculative bubble... With each wave of technology, share prices soared and later fell... The inventions of the late 19th century drove p-e ratios to a peak in 1901, the year of the first transatlantic radio transmission. By 1920 shares prices had dropped by 70% in real terms. The roaring twenties were also seen as a "new era": share prices soared as electricity boosted efficiency and car ownership spread. After peaking in 1929, real share prices tumbled by 80% over the next three years." (The Economist, September 21, 2000, Bubble.com)

and financial development across countries, and find that financial frictions account for a significant proportion of cross-country differences in several aggregates, including output per worker, aggregate TFP, sector-level productivity, and capital to output ratios. [Khan and Thomas, 2013] take into consideration both aggregate and individual productivity shocks. They find that a negative shock to borrowing conditions while generate differences, in terms of recessions and recoveries, when compared to an exogenous shock to total factor productivity. [Buera and Moll, 2015] consider a model with three different types of heterogeneity: efficiency (TFP), investment, and labor wedges, and find that a credit crunch emerges as a different wedge. In their case, however, they consider that the TFP shocks are i.i.d., and that agents are able to observe this shock one period in advance, giving them the ability to adapt their behaviour accordingly. This causes their distribution to be constant over time, unlike in our model. [Arellano et al., 2017] consider an idiosyncratic shock in intermediary firms, with the goal to measure the output costs of sovereign risk. [de Ferra, 2016] and [Kaas et al., 2016] incorporate this characteristic in studying the interaction between firms' financial frictions and sovereign default risk. Other papers take a more empirical approach, and use producer, firm or sector level data. [Midrigan and Xu, 2014] resort to producer-level data to evaluate the role of financial frictions in determining total factor productivity, and conclude potential significant losses from inefficiency low levels of market entry and technology adoption. [Bloom, 2009] resort to 'standard deviation of Industry-level TFP growth', which is measured on an annual basis using the NBER industry database. [Basu et al., 2006] construct a measure of aggregate technology change, taking into account aggregation effects, changing utilization of capital and labor, non-constant returns, and imperfect competition, and find technology improvements have a contractionary effect on inputs, investment and output in the short run. In [Hornbeck and Moretti, 2019], the authors measure total factor productivity using confidential plant-level data from the Census of Manufacturers (CMF) in 1977, 1987, and 1997. [Chen and Gornicka, 2020] resort to [Beaudry and Portier, 2006] U.S. TFP news shocks based on short-run and long-run restrictions, which are updated by Valerie Ramey[17].

3.4 III - Model

In this section, we develop a quantitative dynamic stochastic partial equilibrium model, which explores the impact of short-term and long-term borrowing on firm's balance sheets, on the different variables, subjected either to earnings based or collateral constraints. The model economy comprises of one central agent, the firms, and the trigger for heterogeneity in this agent will be the persistent differences in their idiosyncratic productivity shocks, as well as the financial constraints they are subjected to, and the maturity of the debt. The differences will be further exacerbated through the different choices that the firms make, specifically, regarding capital, borrowing, and labor. It is important to point out, however, that, in this model, the firms do not

[17] Available at https://econweb.ucsd.edu/ vramey/research.html#data

choose the type of financial constraint that they are subjected to, nor the maturity of the debt, nor the productivity shock. Even though these will be different among firms, they will take these elements as given, and make the choices for the remaining variables. Finally, despite the fact that firms do not choose their productivity level, given that they have different productivity levels, and we are able to infer on our main objective: to see if short-term debt has a higher negative impact on productivity for firms with earning based constraints, when compared with firms with asset-based constraints. For this end, we take a similar approach to the model described in [Hatchondo and Martinez, 2009].

3.4.1 Firms

The economy consists of a unit mass of small firms. Each firm produces a homogeneous output, employing labor n and using predetermined capital stock k, according to a Cobb-Douglas decreasing returns to scale production technology:

$$y = \theta k^{\alpha} n^{\nu}, \quad with\, \alpha, \nu > 0 \quad and \quad \alpha + \nu < 1 \tag{3.2}$$

where θ is an exogenous firm specific productivity shock.

We assume that the idiosyncratic shocks follow a standard stochastic process, with normal innovations:

$$ln(\theta_t) = \rho ln(\theta_{t-1}) + \xi_t \quad \sim N(0, \sigma^2) \quad i.i.d. \tag{3.3}$$

At the beginning of each period, every firm starts with a stock of capital k, inherited debt b, and productivity level θ. Thus, the firm type is identified with the three state variables (k; b; θ). We assume that time t = 0 values of these four states for every firm are the same, so ex-ante all firms are identical. As we explained before, the firms will be divided in 4 groups, according to the 2 possible constraints, and the 2 possible maturities of debt.

3.4.2 Timeline

For clarification, we will also include a timeline for the decisions and events that are either chosen or will influence the decisions of the firm[18].

The timing of events within each period is as follows:

1. At the start of period t, the firm inherits capital $k_{i,t} \in \mathbf{K} \subset \mathbf{R}_+$. The firm is then, subjected to the idiosyncratic shock on TFP (Total Factor Productivity), $\theta_{i,t}$.

2. The firm chooses the level of employment and production, paying labor costs, and repaying existing debt. Continuing firms undertake production by hiring labor $n_{i,t}$ at wage rate

[18] We use the time subscript t and the firm subscript i to make this distinction more explicit

w to earn revenues given by:

$$\pi_{i,t}(k_{i,t},\theta_{i,t}) = \max_{\{n_{i,t}\}} \{\theta_{i,t}k_{i,t}^{\alpha}n_{i,t}^{\nu} - wn_{i,t}\} \tag{3.4}$$

The choice of labor is, thus, independent of the debt levels $b_{i;t}$. Optimal values of output and labor can be derived by solving this static optimization problem.

3. At the end of the period, the firm will choose investment, and, thereby, next period capital $k_{i,t+1}$. The evolution of capital is given by:

$$k_{i,t+1} = (1-\delta)k_{i,t} + i_{i,t} \tag{3.5}$$

where $\delta \in (0,1)$ corresponds to the rate of capital depreciation.

We will also consider the firm faces capital adjustment costs. The traditional capital-investment model assumes convex cost's function, as described in [Cooper and Haltiwanger, 2006]. In our case, we resort to a quadratic cost specification:

$$AC(k_{i,t+1},k_{i,t}) = \frac{\gamma}{2}([k_{i,t+1}-(1-\delta)k_{i,t}])^2 \tag{3.6}$$

4. The firm also chooses the next period debt level $b_{i,t+1} \in \mathbf{B} \subset \mathbf{R}$. As we discussed before, there will be firms with only the option to contract short-term debt, and others with only the option to contract long-term debt.

   (a) We begin with the firms with the option of short-term debt. Debt is a one period contract between the firm and the lender. A loan of $b_{i,t+1}$ implies a debt of $q_0 b_{i,t+1}$ to be repaid in the next period. q_0 is, thus, the gross interest rate on the loan. Any revenues obtained after deducting for next period capital, investment adjustment costs and debt expenses is paid as dividends:

$$D_{i,t}(k_{i,t},b_{i,t},\theta_{i,t}) = \pi_{i,t}(k_{i,t},\theta_{i,t}) - i_{i,t} - AC(k_{i,t+1},k_{i,t}) + b_{i,t+1} - q_0 b_{i,t} \tag{3.7}$$

   (b) For firms with long-term debt, the condition will be very similar, with only the borrowing component changing:

$$D_{i,t}(k_{i,t},b_{i,t},\theta_{i,t}) = \pi_{i,t}(k_{i,t},\theta_{i,t}) - i_{i,t} - AC(k_{i,t+1},k_{i,t}) - q_0 b_{i,t} + [b_{i,t+1}-(1-\lambda)b_{i,t}] \tag{3.8}$$

   where the term $[b_{i,t+1}-(1-\lambda)b_{i,t}]$ represents the borrowing decision, as in [Hatchondo and Martinez, 2009]. For example, if the firm chooses $b_{i,t+1} = (1-\lambda)b_{i,t}$, it implies that it is neither borrowing nor lending. In other words, the amount of coupons that will mature next period are solely determined by past debt issuances. On the other hand, if $b_{i,t+1} < (1-\lambda)b_{i,t}$, then the firm is issuing new bonds (borrows), and if $b_{i,t+1} > (1-\lambda)b_{i,t}$, the firm is purchasing bonds (saving). For simplicity, we will assume that $b_{i,t+1} \leq (1-\lambda)b_{i,t}$, such that the firm is only able to borrow.

There is a non-negativity constraint on dividends $D(.) \geq 0$. If we allowed for negative dividends, this would imply the firms would be able to use equity to counteract financial frictions in the debt lending market, and would prevent us from understanding the effects of imperfect debt markets could have on the firms decisions.

5. The choice of the debt amount will be subjected to the constraints that are faced by each firm, which will be either on the earnings, or on the assets:

   (a) Earnings based constraint: $b_{i,t+1} \leq \varepsilon_\pi \pi_{i,t}$

   (b) Asset based constraint: $b_{i,t+1} \leq \varepsilon_k (1-\delta) k_{i,t}$

In the earnings based constraint, for a certain level of the debt, the choice for capital of the firm in the next period will affect the distribution of its earnings and its ability to repay the debt. In the asset based constraint, the effect is more direct, where the choice of capital will impact the firm's ability to repay the debt. We will be expecting the impact to be different, according to the constraints that the firm as to abide by.

As we stated before in point 1, the different levels of capital will result from the different shocks the firms were subjected to, as well as the different decisions made for inputs and borrowing in previous periods. We assume that the shock θ follows a Markov chain, with $\theta \in E \equiv \{\theta_1, ..., \theta_{N_\theta}\}$, where $Pr(\theta' = \theta_j | \theta = \theta_i) \equiv \pi^\theta_{ij} \geq 0$ and $\sum_{j=1}^{N\theta} \pi^\theta_{ij} = 1$ for each $i = 1, ..., N_\theta$.

Regarding the capital adjustment cost, as we can see in point 3, this cost will depend on the capital amount of the firm, as well as the level of investment. This framework for the capital adjustment costs will make them state dependent, that is, they will vary according to the idiosyncratic shocks faced by the firm's, which will affect their capital accumulation, as well as their decision for investment in capital for the next period.

3.4.3 Optimal labor and production

In order to solve the firm's problem, we need to start with the decision of the choice of labor and production in point 2:

$$n(k,\theta) = \left(\frac{\nu\theta k^\alpha}{w}\right)^{\frac{1}{1-\nu}} \tag{3.9}$$

$$y(k,\theta) = (\theta)^{\frac{\nu}{1-\nu}} \left(\frac{\nu}{w}\right)^{\frac{\nu}{1-\nu}} (k)^{\frac{\alpha\nu}{1-\nu}} \tag{3.10}$$

and the flow of profits net of labor costs becomes,

$$\pi(k,\theta) = (1-\nu)\, y(k,\theta) \tag{3.11}$$

These values will be the same for all firms with common values of (k, θ) that choose to keep producing, given their initial state of (k, b, θ).

3.4.4 Value function of the firm

Even if firms select the same amount of capital (k_{t+1}) and debt (b_{t+1}), they will not have the same amount of cash flows and resources for next period, due to the uncertainty of the idiosyncratic Total Factor Productivity (TFP) shock (θ_{t+1}). And with a specific idiosyncratic Total Factor Productivity shock, the firms choose a specific level of debt (b_{t+1}) as well as a specific level of next period capital k_{t+1}, and will pay $q_0(b_{i,t+1})b_{i,t+1}$ units in the next period. The gross interest rate of the loan, given by $q_0(b_{i,t+1})$, is, then, determined based solely on the firms borrowing amount. On the choice of borrowing amount, the fact that they are subjected to different constraints and maturities on the debt will lead to different choices of the borrowing amount.

The dynamic problem for the firms can be described as follows:

$$V(\theta_{i,t}, k_{i,t}, b_{i,t}) = \max_{\{i_{i,t}, b_{i,t+1}\}} [D_{i,t} + \beta E[V(\theta_{i,t+1}, k_{i,t+1}, b_{i,t+1}) | \theta_{i,t}, k_{i,t}, b_{i,t}]] \tag{3.12}$$

The goal is to maximize the discounted sum of the dividends (or the present value of the dividends), subject to the choice for capital and for borrowing being in the firm's feasible capital and debt combinations, and the cash flows for the next period result from the choices of borrowing and capital, as well as the transition of the TFP shock. Recall that the firms will be subjected to the different dividend functions that we described in point 4, and the different constraints described in point 5 in subsection 3.4.2.

3.5 Calibration

In this section, we describe our calibration strategy in setting the structural parameters.

The discount factor for future periods, given by β, is set to 0.96, to imply a real interest rate of 4%, consistent with the values established by [Gomme et al., 2008]. We follow with the labor share of income in the production function, ν, and establish a value of 0.60, according to [Cooley and Prescott, 1995]. As for the depreciation rate of capital, δ, is defined for the value of 0.069. The chosen value corresponds to the average value of the investment to capital ratio for private capital stock between 1954 and 2002 in the US Fixed Asset Tables (considering economic growth). We define the capital share of output, α, at 0.256, and the investment adjustment costs parameter, γ, at 0.2.

Next, we explain how we estimated the firm-specific shocks, and the corresponding probabilities. We start by defining the different elements which create the Normal distribution for the joint process of the shocks, and then discretize the state space using a Markov Chain, and obtain the corresponding probabilities[19]. In our estimation exercise, we define 3 states for the idiosyncratic shock, that is, $N_\theta = 3$. As for the choice of the calibrated values, we rely on [Khan et al., 2017]. The unconditional mean of process is defined as $\mu_\theta = 0$, that is, the distribution of the shock is established such that, on average, each of the shocks has a value equal to 1 (notice that this implies that the shock has no impact on the decision of the firm). We set the standard deviations of innovations defined as $\sigma_\theta = 0.0499$, and the probability of repeating the firm specific shock as $\rho_\theta = 0.757$.

Since we are considering a partial equilibrium model, we also proceed with the calibration of some of the prices. In order to simplify, we consider the wage, $w = 1$. This would imply that we are considering just overall employment in the production function. We consider that the gross interest rates charged, q_0, change according to the borrowing amount. We define a 21-point grid, whose values are between 1.01 and 1.05 (thus, the net interest rates between 1% and 1.05%). In [Hatchondo and Martinez, 2009], a gross interest rate of 1.01 is considered.

For the capital and the borrowing grids, we consider a 21-point grid. Both lower bounds are taken from [Khan et al., 2017]. The lowest capital value is set at $k_0 = 0.063$, and the lowest borrowing amount is set at $b_0 = 0.046$. The values for the proportion of assets and earnings in the constraints are taken from [Drechsel, 2023], which define the $\varepsilon_k = 0.37$ and $\varepsilon_\pi = 4.6*4$, respectively. The last element is taken from [Hatchondo and Martinez, 2009], and regards the additional element in the long-term debt, set at $\lambda = 0.053125$.

The summary of the values used in the calibration are described in the following table:

Table 3.5: Parameter Values

β	ν	δ	α	μ_θ	σ_θ	ρ_θ	N_θ
0.96	0.6	0.069	0.256	0	0.0499	0.757	3
γ	w	q_0	k_0	b_0	ε_π	ε_k	λ
0.2	1	1.01-1.05	0.063	0.046	0.37	4.6*4	0.053125

[19]The Tauchen method is used for this estimation.

3.6 Results

3.6.1 Policy Functions - Short-term Debt

In this section, we provide a description of the results we have obtained, for the short-term debt scenario, starting with the policy functions.

In Figures 3.3, 3.4, and 3.5, in the Appendix, we have the net borrowing (that is, difference between borrowing of next and current period, taking into account the cost), for the different possible productivity shocks. This is for firms with access to short-term debt, and either unconstrained, earnings-based constrained or asset based constrained, respectively. In the first case, we have the estimations if the firms are unconstrained, the second case for the firms with asset based constraints, and the third case for the firms with earnings-based constraints.

For the different scenarios, it seems that the net borrowing decreases with the amount of capital, as well as the amount of borrowing. This is the case for the different productivity shocks, as well as the different constraints. There are 2 opposite effects that higher capital could have on borrowing: 1 - Since the firm has more resources, it could choose to expand the borrowing, while still guaranteeing dividends and enough resources to repay, and avoid depreciation and investment adjustment costs (this would entail a more complementary effect of debt); 2 - On the other hand, the firm could use debt when it has less resources. This would guarantee a higher smoothing of dividends throughout the different periods (this would entail a more substitutionary effect). From the behaviour of the series, we can see that there is a predominance of the second effect. That is, firms use debt to substitute capital and smooth dividend distribution throughout the different periods, in order to maximize their value function. As firms accumulate more capital, they do not need as much debt, as capital itself is able to boost production, profits and dividends. Additionally, this could also be related to the cost of debt. Since the cost per unit increases with the amount of debt, firms would prefer not to accumulate large amounts of debt. However, we also tested this for the case of a constant interest rate, and the behaviour is relatively similar, which would seem to imply that the main reason is that firms use debt as a substitute for capital.

In terms of the impact of the constraints, we begin with the earnings-based constraint. In this case, we can see that there is a clear difference in borrowing between the high value shock and the other 2 scenarios. This is likely due to the constraint allowing higher borrowing for firms with higher TFP. Recall that the constraint applies a ceiling on the borrowing amount based on a proportion of the profits. With a higher level of productivity, the firm is able to achieve higher profits, for the same level of capital and borrowing. Thus, it is able to borrow higher amounts. This also seems to be consistent with our empirical data, in which short-term borrowing seems to have a negative correlation with the Total Factor Productivity, when imposing IC constraints. The other 2 productivity scenarios within the earnings-based constraint seem to close to one another, although the medium TFP has a slightly higher net borrowing, compared to the low

TFP.

When we shift to the analysis of the LEV constraint scenarios, we can see that, even though there is a difference between the 3 TFP shocks, these are more in terms of volatility, the average value seems to be the same across the different scenarios. This is also in accordance with our empirical results, in which short-term debt does not seem to hold an additional impact on productivity, when firms are subjected to asset-based constraints, and the volatility associated with this additional term is also higher, when compared to IC constraint coefficient and the unconstrained coefficient. There also seems to be higher extremes in the unconstrained scenario, which would likely result from higher margin to choose the debt levels to smooth dividend distribution.

We follow with an analysis to the other policy functions, namely, labor and investment, displayed in Figures 3.6, 3.7, respectively. As expected, the choice of labor is increasing in capital (given that labor is an additional input for production), they act as complementary in the production process. As a result, in order to achieve higher productivity and profitability, the increase in capital needs to be accompanied by the increase in labor. Recall that, in the case of a Cobb-Douglas production function, as capital increases, the marginal productivity of capital decreases, and the marginal productivity of labor increases. The higher values of the shock also lead to a choice for higher labor, as expected, since they will increase productivity and profitability. The choice for labor seems to be concave in capital. This is simply a reflection of the optimal condition for labor, which is concave in capital (due to the share of capital income).

In terms of investment, we can see that it is decreasing in capital, for all values of the productivity shock. Recall that, since we have a concave profit function, the marginal profit of capital is decreasing. So, further increases of capital will result in lower increases of profits, and, therefore, dividends. Also, higher levels of capital will result in higher depreciation costs, and higher investment needs resulting in higher adjustment costs.

We end our initial analysis with the value function, since it consists of the discounted sum of the dividends of the firm, in Figure 3.8. As expected, the dividend amount is increasing in the amount of capital. The goal of the firm will be to smooth dividends distribution over time, decreasing volatility (and risk) in their income overtime, as typical firms/shareholders are risk averse. Therefore, in order to achieve higher levels of dividends, and be able to stabilize those levels overtime, they will have to resort to high capital accumulation and investment as well. Also, a higher level of the productivity shock will lead to an increase of the dividend amount, for the same amount of capital in the next period, or an increase in the capital amount, for the same level of dividends. A higher value of the shock will increase the productivity and profits, for the same level of capital, leading to an availability of more resources to be applied in capital investment, or to be distributed as dividends. However, notice that the dividends are concave in the amount of capital. This results from the diminishing returns to scale for capital, as well as the increasing costs of capital. As capital increases, on one hand, the increases in the firm's profits will be smaller and, on the other hand, the costs are either constant (due to the depreciation rate), or increasing (due to the capital adjustment costs).

Notice that, for the different policy functions, with the exception of the borrowing, we did not distinguish between the constraint scenarios. The main reason is that there did not seem to be a significant difference for the remaining policy functions, but this is something we are going to explore in more detail in the simulation subsection below. This is also in accordance to our empirical findings, in which financial constraints did not seem to lead to a significant difference in labor, capital or investment (or the difference could be explained by other factors). The remaining option is, thus, in the value function, as we can see in Figure 3.9. That is, as the firm is more limited in its borrowing ability, it lowers the dividend distribution, instead of changing the investment, capital or labor policy.

3.6.2 Policy Functions - Long-term Debt

In this subsection, we provide a description of the results we have obtained, for the long-term debt scenario, starting with the policy functions. If we take a look at Figure 3.10, which shows the net borrowing in the case of long-term debt, we can see a very different behaviour, when compared to the short-term debt. First, there is no distinction between the different productivity shocks. This would imply that the optimal borrowing amounts selected are always the same, for the different productivity shocks. Second, net borrowing amounts are much lower, both on the upper and lower end. This would imply that the changes in the borrowing amount have a lower volatility in this scenario, and are more consistent, for the different levels of capital. Third, there seems to be more stability in the series for lower values of capital. All these elements seem to point for a constraint on the ability of firms to change their borrowing, or the constraint itself leads the firms to optimally choose to lower their volatility, in changing their borrowing amounts. Our results on the value function would point to the first option. In terms of the investment and labor, there is no change to these policies, when compared to the short-term borrowing.

Thus, the adjustment by the firms is done through the value function, as we can see in Figure 3.11. Since firms are not able to freely adjust their borrowing, the value function that they are able to attain is lower, for all levels of capital. This would imply that firms sacrifice dividends when they are not able to borrow freely, instead of changing investment or labor.

In terms of the impact of the earnings-based or the asset-based constraints, they do not seem to exert an impact on the estimations. Although this would seem to be consistent with our empirical data, in the sense that the different covenants do not exert an impact on long-term debt, we take caution on extrapolating additional insights, as there are other possible reasons for this result.

3.6.3 Simulations

In this final subsection, we provide simulations with our partial equilibrium model estimations, provided in Table 3.27, and compare with the empirical data described in section 3.2.6. We have the same summary statistics analysis, for 5 main variables: employment, capital, investment, short-term debt, and long-term debt. As we can see, the main differences between the constraints are within the short-term debt. Firms with earnings-based constraints accumulate a lower amount of short-term debt, when compared to firms with asset based constraints, or unconstrained. This is consistent with our data, which showed that firms with IC covenants (which we consider as a proxy for earnings-based constraint) have lower levels of short-term debt, when compared with either firms with LEV covenants (which we consider as a proxy for asset-based constraints), or unconstrained firms. This difference was robust to different controls, including for firm size and age.

On the other hand, the other variables do not seem to show a difference across constraints, which is also consistent with our data (there either were no differences, in the case of investment, or the differences were not robust to the controls introduced). Notice that we did not include the estimations of the productivity shocks in the simulation results. The main reason is that this shock is exogenous in our process, and the estimations are likely to be similar, given that inputs of the estimation of the different scenarios were the same.

3.7 Conclusion

Financial frictions play a central role in the economy, by constraining the firm's ability to resort to borrowing funds. [Diamond and Dybvig, 1983] are among the first papers to point out the importance of this characteristic, by pointing out the vulnerability of the financial system to bank runs, and it's potential self-fulfilling component. [Gertler and Gilchrist, 2018] provide a summary of the contribution of research incorporating market frictions, how they may generate financial crisis and how it can be transmitted to the real sector. On the other hand, the imposition of financial constraints can also have an advert effect on economic growth, by limiting firm's access to additional funds, impacting their productivity, and reducing their investment and profitability.

Traditionally, the literature has simplified the modelling of the debt capacity of the firms according to their market leverage[20]. However, in reality, the firms can have different explicit constraints on the amount of borrowing, or even a combination of different constraints, which can be very different from establishing a maximum for the market leverage. We consider the impact of borrowing constraints through loan covenants, which consist of provisions in debt contracts that constrain future lending. They circumscribe a set of actions a borrower may take

[20] Recall the financial accelerator component in [Bernanke and Gertler, 1999] that we discussed before.

(nonfinancial covenants) or specify minimum or maximum thresholds for cash flows or balance sheet variables (financial covenants). In our case, mostly due to data availability and summarizing purposes, we focus on the role of financial constraints. Thus, the choice for the different characteristics associated with the constraints are likely to yield different impacts, including the amount, maturity, interest rate charged, type of covenant(s) and variables chosen, limits set, and stipulation of covenant violation. In the case where a borrower either is unable or chooses not to comply with the covenant, they enter technical default and the lender is able to accelerate the repayment of the loan, force renegotiation of the loan, or waive or reset the covenant with no further impact on the loan. In the case of this chapter, we group the different covenants into 3 main groups: Interest coverage (IC), Debt-to-earnings (DE), and Leverage (LEV), with a particular focus on the Interest coverage (IC) and Leverage (LEV) covenants. Even though IC covenants, and especially financial covenants in general, are very common, there are still significant uncertainties that remain about how the structure of these covenants/constraints influences macroeconomic dynamics. In this paper, we evaluate how the different functional forms of these covenants can affect productivity and the borrowing structure of the firms.

To motivate our topic, we construct a dataset at the firm-year level by merging the syndicated loan data, provided by Refinitiv LPC DealScan ("DealScan"), with the firm level data, provided by the Center for Research in Security Prices (CRSP)/Compustat Merged Database ("CCM"). In terms of number of facilities/loans, we have a total of 171,752 different facilities that originated between 1982 and 2022. Of the firms which contain information regarding the covenants associated to the loans, around 76% include IC covenants, and around 18% include LEV covenants. This would match the composition of datasets in similar papers. [Lian and Ma, 2021] combine different data sources, and show that only 20% of credit to US firms is asset-based, while 80% is earnings-based. [Greenwald, 2019] focus on constraints where the interest payments are restricted by earnings, which are often associated with earnings-to-debt restrictions (these would be the Interest Coverage(IC) constraints that we have discussed). They also calculate that they are present in over 80% of firms with covenants. Thus, we consider that there is a significant overlap (or similarity) between the IC covenants and earnings-based constraints.

We conduct an analysis on firms subjected to different covenants, and find that firms with earnings-based constraints have lower levels of TFP (Total Factor Productivity), and short-term debt, when compared to firms with asset-based constraints. The data also shows that this is connected to an additional negative impact that short-term debt has on the productivity for the firms with earnings-based constraints, which does not verify in the firms with asset-based constraints. Both these characteristics are robust to the use of 3 different TFP estimation methods, different subsamples, and additional controls, including age and size of the firm. Other characteristics, including total assets, or long-term debt, seem to be caused by differences in the size of the firms, and not due to the different covenants.

Thus, we consider a quantitative dynamic stochastic partial equilibrium model, with three main types of firms, distinguished by their constraints, which explores the impact of short-term and long-term borrowing on firm's balance sheets, on the different variables. We construct replications for this theoretical model, and assess the how well it fits our actual data.

Our findings show that constraints exert an impact on short-term borrowing, but not on the remaining variables. More specifically, firms that face an earnings-based constraint show lower levels of short-term borrowing, compared with firms that are either unconstrained, or asset-based constraint. The adjustment is made through lower dividend distribution, as can be seen by the lower values of the value function. They also point to the impact being larger for firms with lower productivity shocks, which is in accordance with our empirical findings. Even though that our data shows differences in some of this variables (for example, on long-term debt), these were not robust to some of the controls, including the size of the firm.

In terms of directions for future research, we would consider moving towards a general equilibrium model, as some of these results may be a reflection of the calibrated values. We also believe that there is need to endogenize the productivity shock. In our case, this process is exogenous, and a reflection of the chosen calibration. Thus, we are unable to evaluate whether there is a direct impact of short-term debt on the productivity of the firm.

3.8 Appendix

3.8.1 Additional Tables

Table 3.6: DealScan-CRSP logit coefficients

Dependent variable	[Chava and Roberts, 2008] match
Name match indicator (Jaro-Winkler distance)	30.973*** (3.666)
State match indicator	3.572*** (0.793)
Industry match indicator	3.643*** (0.812)
Constant	-34.617*** (3.109)
Observations	999,461
Log-likelihood	-46.442
AIC	100.88
Null deviance	340.925
Residual deviance	92.883
Deviance Residuals	
Min	-1.7936
1Q	-0.0010
Median	-0.0004
3Q	-0.0002
Max	5.4679

Notes: Regressors are estimated based on the 1 million sample of randomly drawn pairs of records from DealScan and Compustat. The dependent variable is 1 if the randomly paired loan facility ID and firm ID combination were found in [Chava and Roberts, 2008] and 0 otherwise. Jaro–Winkler distance is the string similarity between the company names from DealScan and Compustat, respectively. State and industry indicators are 1 if the DealScan and Compustat records match by state and NAICS code, respectively. Standard deviations are included in (). *p < 0.1; **p < 0.05; ***p < 0.01.

Table 3.7: Data description: Sales - Total

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Total						
25%	40.93	56.36	118.50	56.36	118.50	32.20	246.68	215.69	57.57	95.95	199.48	49.90
Median	175.43	199.70	252.61	349.67	237.55	187.54	456.97	265.34	199.70	305.29	684.50	205.18
75%	650.97	650.98	701.13	1,073.5	682.96	710.10	1,384.87	835.19	617.51	718.70	1,350.20	710.10
Mean	937.91	649.48	614.79	1,047.48	524.14	747.69	1,531.43	1,069.19	642.48	853.01	1,416.01	860.57
Std. Dev.	2,776.96	1,445.27	1,257.88	1,941.23	985.21	1,531.83	2,440.81	2,544.47	1,500.98	1,918.07	2,310.23	2,317.30
Skewness	8.40	5.90	6.90	3.88	7.96	3.72	2.64	3.51	6.48	5.22	3.63	8.62
Kurtosis	111.86	49.19	61.60	24.39	84.08	18.64	9.96	13.60	56.42	32.80	21.54	128.31

Notes: In this table, we provide information on sales (code SALE, in million US$) on our total sample, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.8: Data description: Debt/Assets

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Total						
25%	0.13	0.19	0.25	0.16	0.26	0.16	0.15	0.18	0.19	0.23	0.17	0.16
Median	0.29	0.33	0.38	0.29	0.42	0.29	0.26	0.32	0.33	0.34	0.29	0.31
75%	0.43	0.48	0.54	0.40	0.58	0.41	0.47	0.47	0.48	0.45	0.39	0.45
Mean	0.30	0.36	0.42	0.30	0.44	0.30	0.32	0.35	0.37	0.35	0.29	0.33
Std. Dev.	0.23	0.28	0.29	0.70	0.30	0.20	0.21	0.22	0.30	0.25	0.17	0.25
Skewness	1.59	3.50	3.64	0.70	2.84	0.73	1.23	1.10	3.80	7.73	0.60	2.79
Kurtosis	12.58	30.48	41.60	3.92	20.84	3.91	4.31	3.88	32.26	172.11	3.74	27.45

Notes: In this table, we provide information on Total Debt (code DLC+DLTT, in million US$) divided by Total Assets (code AT, in million US$), for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.9: Data description: Debt/EBITDA

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Total						
25%	0.94	1.29	1.67	1.14	1.75	1.14	1.14	1.62	1.24	1.54	1.21	1.18
Median	2.34	2.63	3.09	2.50	3.33	2.42	2.35	2.35	2.58	2.47	2.68	2.48
75%	4.34	4.35	4.35	4.12	4.71	4.31	3.70	3.70	4.30	3.59	3.89	4.31
Mean	3.90	3.17	3.84	3.37	4.10	3.36	2.67	2.98	2.91	3.12	3.40	3.57
Std. Dev.	23.33	19.38	7.24	13.07	8.11	12.24	2.50	2.65	22.66	3.74	14.23	21.02
Skewness	-4.76	-64.15	49.55	17.22	47.40	-25.15	5.38	5.69	-60.90	5.61	55.75	-21.25
Kurtosis	7,051.32	8,435.96	4,231.81	3,949.88	3,626.78	2,311.65	52.90	53.22	6,875.69	46.74	5,060.31	7,883.95

Notes: In this table, we provide information on Total Debt (code DLC+DLTT, in million US$) divided by EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortization, code OIBDP, in million US$), for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.10: Data description: EBITDA/Assets

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Total						
25%	0.08	0.09	0.10	0.08	0.10	0.08	0.11	0.09	0.10	0.11	0.08	0.09
Median	0.12	0.13	0.13	0.12	0.13	0.12	0.14	0.13	0.13	0.14	0.12	0.13
75%	0.17	0.18	0.18	0.16	0.18	0.16	0.19	0.20	0.18	0.17	0.16	0.17
Mean	0.13	0.14	0.15	0.13	0.14	0.13	0.14	0.14	0.15	0.15	0.13	0.14
Std. Dev.	0.08	0.08	0.07	0.07	0.08	0.07	0.06	0.06	0.08	0.07	0.07	0.08
Skewness	2.28	1.79	1.93	1.31	1.80	1.46	0.13	0.22	1.86	2.43	1.03	2.06
Kurtosis	20.00	9.47	10.80	7.34	8.61	8.00	2.90	2.79	9.84	18.88	5.96	15.97

Notes: In this table, we provide information on EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortization, code OIBDP, in million US$), divided by Total Assets (code AT, in million US$), for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.11: Data description: Log of Assets

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Total						
25%	5.35	5.79	6.14	5.92	6.14	5.34	5.70	4.83	5.74	6.04	7.10	5.60
Median	6.83	7.05	7.39	7.62	7.38	7.04	7.05	6.71	6.99	7.53	8.60	7.04
75%	8.48	8.40	8.57	9.27	8.45	8.48	9.26	7.93	8.37	8.57	9.81	8.57
Mean	6.92	7.02	7.36	7.42	7.35	6.86	7.28	6.66	7.00	7.33	8.20	7.04
Std. Dev.	2.22	1.88	1.67	2.22	1.58	2.11	2.12	1.96	1.85	1.91	2.14	2.11
Skewness	0.11	-0.19	-0.01	-0.40	0.02	-0.24	-0.03	0.41	-0.14	-0.02	-0.81	-0.03
Kurtosis	2.70	2.71	2.73	2.48	2.54	2.43	1.95	2.55	2.72	2.84	3.20	2.69

Notes: In this table, we provide information on the log of Assets (code AT, in million US$) on our total sample, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.12: Data description: Log of Short-term Debt

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Total						
25%	1.09	1.16	1.62	1.68	1.64	1.00	0.22	-0.17	1.15	1.31	3.15	1.20
Median	2.97	3.06	3.31	4.05	3.26	3.08	3.05	1.00	2.94	3.69	5.12	3.14
75%	5.02	4.82	4.90	5.87	4.90	5.25	4.89	4.16	4.69	5.10	6.39	5.08
Mean	3.05	2.96	3.22	3.65	3.17	3.04	2.84	1.98	2.88	3.30	4.52	3.11
Std. Dev.	2.85	2.56	2.49	2.70	2.43	2.68	2.74	2.42	2.54	2.64	2.47	2.73
Skewness	0.03	-0.19	-0.23	-0.48	-0.31	-0.19	0.10	0.48	-0.16	-0.06	-1.00	-0.09
Kurtosis	2.89	2.56	2.64	2.58	2.69	2.39	1.65	2.01	2.58	2.49	3.85	2.76

Notes: In this table, we provide information on the log of Short-term Debt (code DLC, in million US$) on our total sample, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.13: Data description: Log of Long-term Debt

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Total						
25%	3.66	4.37	5.21	4.52	5.24	3.81	3.87	3.87	4.35	4.99	5.68	4.10
Median	5.63	5.94	6.37	6.26	6.39	5.80	5.90	5.41	5.93	6.33	7.24	5.86
75%	7.27	7.26	7.59	7.88	7.61	7.18	6.61	4.16	7.23	7.47	8.60	7.37
Mean	5.33	5.61	6.17	5.89	6.19	5.32	5.80	5.32	5.59	6.05	6.69	5.54
Std. Dev.	2.82	2.41	2.12	2.66	2.06	2.57	2.08	2.00	2.39	2.29	2.57	2.66
Skewness	-0.60	-0.82	-0.89	-0.98	-0.98	-0.82	-0.40	-0.19	-0.75	-0.65	-1.48	-0.73
Kurtosis	3.43	4.00	4.70	3.97	5.09	3.69	3.44	3.89	3.91	3.78	5.52	3.70

Notes: In this table, we provide information on the log of Long-term Debt (code DLTT, in million US$) on our total sample, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.14: Data description: Log of employment

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Total						
25%	-0.05	0.45	0.81	-0.06	0.88	-0.45	0.10	0.10	0.56	0.62	0.54	0.17
Median	1.23	1.59	1.86	1.48	1.73	1.16	1.34	0.50	1.70	1.99	2.05	1.44
75%	2.54	2.73	2.91	2.86	2.73	2.43	3.84	2.53	2.78	3.43	3.35	2.69
Mean	1.22	1.52	1.91	1.34	1.82	0.97	1.77	1.12	1.65	2.10	1.84	1.39
Std. Dev.	1.90	1.74	1.55	2.13	1.34	2.16	2.00	1.67	1.61	2.01	1.96	1.86
Skewness	-0.13	-0.34	0.19	-0.32	0.07	-0.21	0.15	0.34	-0.16	0.12	-0.44	-0.21
Kurtosis	3.01	3.34	2.97	2.80	2.84	2.87	1.76	1.96	2.91	2.35	2.76	3.07

Notes: In this table, we provide information on the log of employment/stock of labor (EMP) on our total sample, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.15: Data description: Log of capital

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Total						
25%	3.57	4.09	4.31	4.23	4.34	3.72	3.87	3.55	4.12	4.21	5.60	3.86
Median	5.28	5.53	5.76	6.41	5.75	5.54	6.11	5.50	5.50	5.81	7.50	5.51
75%	7.02	7.00	7.09	8.09	7.00	7.04	7.84	6.49	6.94	7.09	8.92	7.13
Mean	5.31	5.50	5.79	6.03	5.77	5.43	5.96	5.33	5.47	5.77	6.88	5.49
Std. Dev.	2.47	2.15	1.94	2.57	1.85	2.44	2.33	2.25	2.09	2.15	2.52	2.38
Skewness	-0.04	-0.15	0.10	-0.43	0.12	-0.20	-0.04	0.44	-0.13	0.08	-0.93	-0.12
Kurtosis	2.65	2.89	2.70	2.50	2.67	2.60	2.41	3.21	2.93	2.69	3.20	2.69

Notes: In this table, we provide information on the log of capital (given by PPENT, net value of Total Property, Plant and Equipment) on our total sample, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.16: Data description: Investment rate

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Total						
25%	0.12	0.12	0.12	0.11	0.11	0.12	0.09	0.09	0.12	0.13	0.10	0.12
Median	0.19	0.19	0.19	0.17	0.18	0.18	0.19	0.14	0.19	0.20	0.16	0.19
75%	0.31	0.28	0.28	0.28	0.27	0.29	0.32	0.28	0.28	0.28	0.27	0.29
Mean	0.24	0.22	0.22	0.22	0.21	0.22	0.21	0.19	0.22	0.23	0.20	0.23
Std. Dev.	0.17	0.15	0.13	0.15	0.13	0.16	0.14	0.14	0.14	0.13	0.15	0.16
Skewness	1.65	1.76	1.43	1.78	1.37	1.73	0.72	1.09	1.82	1.73	1.88	1.73
Kurtosis	7.33	8.55	6.66	7.88	6.10	7.74	3.51	4.40	9.12	8.74	8.24	7.92

Notes: In this table, we provide information on the investment rate, which is calculated as investment (code CAPX, in million US$) divided by Stock of Property, Plant and Equipment (code PPENT, in million US$), for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.17: Data description: Log of TFP

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Total						
25%	-0.55	-0.53	-0.43	-0.45	-0.44	-0.54	-0.27	-0.27	-0.54	-0.38	-0.33	-0.52
Median	-0.02	-0.03	0.11	-0.05	0.14	-0.09	-0.06	-0.15	-0.03	0.02	0.03	-0.02
75%	0.53	0.49	0.65	0.46	0.67	0.41	0.18	0.18	0.45	0.60	0.51	0.51
Mean	0.02	0.00	0.08	0.04	0.09	-0.02	-0.05	-0.12	-0.02	0.05	0.13	0.02
Std. Dev.	0.89	0.80	0.74	0.84	0.76	0.86	0.48	0.48	0.13	0.72	0.81	0.85
Skewness	0.21	0.15	-0.06	0.38	-0.16	0.34	0.34	0.63	0.13	0.29	0.50	0.21
Kurtosis	3.71	3.71	3.47	4.10	3.46	3.82	7.01	8.60	3.71	3.50	4.56	3.80

Notes: In this table, we provide information on the log of TFP (Total Factor Productivity) on our total sample, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.18: Data description: Tobin's Q

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Total						
25%	1.10	1.13	1.20	1.08	1.21	1.07	1.08	1.03	1.16	1.15	1.11	1.12
Median	1.40	1.43	1.53	1.30	1.54	1.29	1.40	1.26	1.47	1.50	1.30	1.41
75%	1.98	1.99	2.07	1.68	2.07	1.67	2.06	2.20	2.03	1.98	1.68	1.97
Mean	1.80	1.74	1.77	1.56	1.76	1.53	1.69	1.59	1.81	1.78	1.60	1.77
Std. Dev.	1.40	1.09	1.00	0.92	0.96	0.86	0.80	0.71	1.17	1.11	1.00	1.27
Skewness	6.13	4.33	4.60	6.16	3.99	4.68	1.51	1.25	4.21	5.73	7.45	5.87
Kurtosis	82.07	45.81	44.26	101.10	28.33	46.13	5.55	5.05	45.08	68.78	141.23	80.83

Notes: In this table, we provide information on the Tobin's Q (defined as (AT+(PRCC·CSHO)-CEQ)/AT, where PRCC is the Annual Price Close (fiscal year end), CSHO is Common Shares Outstanding, AT is Total Assets and CEQ is Common Equity, all in million US$) on our total sample, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.19: Data description: Log of Assets - Small and Large firms

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Small						
25%	4.42	4.80	5.28	4.18	5.49	4.18	4.63	4.63	4.91	4.94	4.02	4.55
Median	5.48	5.76	5.99	5.28	6.00	5.32	5.51	5.66	5.77	5.79	5.20	5.60
75%	6.34	6.37	6.35	6.20	6.35	6.21	6.52	6.52	6.41	6.38	6.15	6.35
Mean	5.26	5.47	5.77	5.10	5.84	5.11	5.41	5.43	5.52	5.56	5.05	5.33
Std. Dev.	1.28	1.17	0.89	1.35	0.80	1.33	1.07	1.07	1.13	1.08	1.38	1.24
Skewness	-0.73	-0.98	-1.05	-0.60	-1.06	-0.63	-0.32	-0.34	-0.99	-0.77	-0.51	-0.82
Kurtosis	2.97	3.64	3.82	2.74	4.02	2.82	2.82	2.85	3.72	2.83	2.53	3.18
						Large						
25%	7.72	7.68	7.61	7.90	7.56	7.68	7.93	7.84	7.71	7.67	8.20	7.72
Median	8.63	8.40	8.40	8.91	8.27	8.55	9.13	8.59	8.40	8.57	9.29	8.57
75%	9.75	9.30	9.15	9.85	8.99	9.47	9.69	9.43	9.17	9.46	10.06	9.63
Mean	8.85	8.54	8.51	8.91	8.44	8.63	9.04	8.73	8.54	8.68	9.17	8.76
Std. Dev.	1.32	1.02	1.04	1.16	0.99	1.06	1.12	1.23	1.01	1.15	1.19	1.21
Skewness	0.82	0.58	0.79	0.23	0.63	0.33	-0.03	0.50	0.66	1.09	0.07	0.77
Kurtosis	3.47	2.66	3.24	2.25	2.39	2.02	2.18	2.00	3.00	4.25	2.36	3.44

Notes: In this table, we provide information on the log of Assets (code AT, in million US$), dividing between small and large firms, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.20: Data description: Log of Short-term Debt - Small and Large firms

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Small						
25%	-0.04	-0.01	-0.10	-0.10	-0.10	-0.13	-0.17	-0.17	0.01	0.12	-0.01	-0.03
Median	1.41	1.51	1.65	1.39	1.70	1.31	0.26	0.26	1.57	1.15	1.76	1.47
75%	2.67	2.81	2.92	2.70	2.96	2.48	2.00	2.00	2.84	2.84	3.10	2.74
Mean	1.25	1.37	1.56	1.26	1.61	1.19	0.88	0.88	1.39	1.40	1.50	1.31
Std. Dev.	2.00	1.93	1.95	2.02	1.97	1.90	1.71	1.71	1.93	1.87	2.38	1.99
Skewness	-0.43	-0.34	-0.13	-0.31	-0.18	-0.36	0.94	0.95	-0.36	0.03	-0.34	-0.39
Kurtosis	3.29	2.99	3.28	3.28	3.60	3.28	3.04	3.04	2.77	2.23	2.99	3.18
						Large						
25%	3.51	3.14	3.22	3.97	3.17	3.51	4.16	3.23	3.04	3.69	4.30	3.42
Median	4.96	4.64	4.56	5.45	4.56	4.92	4.89	4.25	4.58	4.74	5.68	4.84
75%	6.46	5.99	5.82	6.40	5.61	6.25	6.39	5.78	5.92	6.32	6.56	6.29
Mean	4.92	4.39	4.36	5.02	4.23	4.67	4.84	3.97	4.33	4.66	5.31	4.75
Std. Dev.	2.33	2.18	2.16	2.00	2.13	2.16	2.07	2.23	2.19	2.23	1.79	2.25
Skewness	-0.26	-0.71	-0.67	-0.89	-0.75	-0.78	-1.05	-0.66	-0.68	-0.52	-0.88	-0.46
Kurtosis	3.74	3.52	3.65	3.85	3.50	3.42	3.87	2.72	3.57	3.90	4.01	3.77

Notes: In this table, we provide information on the log of short-term debt (code DLC, in million US$) on our total sample, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available), dividing between small and large firms. The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.21: Data description: Log of Long-term Debt - Small and Large firms

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Small						
25%	2.06	2.71	3.69	1.95	3.77	2.20	3.49	3.55	2.79	2.99	1.01	2.27
Median	3.82	4.36	4.79	3.56	4.94	3.66	3.87	3.87	4.41	4.35	3.22	4.06
75%	5.04	5.42	5.63	4.84	5.63	4.86	5.30	5.30	5.42	5.49	4.83	5.20
Mean	3.32	3.84	4.35	3.13	4.46	3.26	4.14	4.19	3.93	4.00	2.70	3.52
Std. Dev.	2.24	2.04	1.80	2.21	1.76	2.11	1.39	1.37	2.01	1.86	2.49	2.18
Skewness	-1.01	-1.14	-1.45	-1.01	-1.67	-1.04	-1.42	-1.52	-1.12	-0.90	-0.81	-1.06
Kurtosis	3.90	4.34	5.32	3.82	6.33	4.09	8.32	9.01	4.30	3.36	2.99	4.05
						Large						
25%	6.34	6.37	6.58	6.42	6.62	6.25	6.61	6.43	6.36	6.47	6.72	6.37
Median	7.29	7.21	7.37	7.41	7.29	7.18	7.37	6.97	7.22	7.47	7.80	7.27
75%	8.45	8.08	8.09	8.43	8.07	8.08	8.26	8.58	8.09	8.09	8.87	8.33
Mean	7.35	7.20	7.37	7.42	7.36	7.15	7.35	7.19	7.18	7.40	7.66	7.32
Std. Dev.	1.65	1.41	1.29	1.37	1.28	1.30	1.26	1.37	1.47	1.34	1.38	1.54
Skewness	-0.38	-0.62	-0.30	-0.42	-0.56	-0.47	-0.55	-0.66	-0.65	0.37	-0.49	-0.44
Kurtosis	4.72	6.03	5.98	3.86	6.32	4.95	5.09	4.98	6.11	5.04	3.24	5.10

Notes: In this table, we provide information on the log of long-term debt (code DLTT, in million US$), dividing between small and large firms, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.22: Data description: Tobin's Q - Small and Large firms

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Small						
25%	1.09	1.13	1.26	1.07	1.27	1.06	1.10	1.10	1.15	1.16	1.10	1.11
Median	1.43	1.45	1.58	1.34	1.60	1.34	1.98	1.99	1.46	1.54	1.36	1.44
75%	2.08	2.04	2.10	1.86	2.08	1.77	2.48	2.48	2.10	2.58	2.10	2.07
Mean	1.88	1.85	1.94	1.68	1.92	1.62	1.81	1.81	1.92	2.00	1.89	1.87
Std. Dev.	1.58	1.33	1.33	1.20	1.29	1.02	0.73	0.70	1.41	1.45	1.62	1.49
Skewness	6.25	3.98	3.96	6.04	3.39	4.66	0.97	0.66	3.86	5.05	6.21	5.68
Kurtosis	83.98	37.58	29.94	85.73	17.93	42.95	5.43	4.15	37.63	50.16	81.90	74.47
						Large						
25%	1.11	1.14	1.15	1.09	1.15	1.08	1.03	0.98	1.18	1.13	1.12	1.13
Median	1.37	1.42	1.50	1.29	1.51	1.26	1.26	1.07	1.47	1.48	1.30	1.37
75%	1.88	1.94	2.04	1.61	2.07	1.57	1.87	1.24	1.99	1.84	1.61	1.87
Mean	1.71	1.64	1.64	1.50	1.64	1.47	1.58	1.23	1.70	1.62	1.51	1.66
Std. Dev.	1.17	0.79	0.64	0.69	0.60	0.68	0.85	0.59	0.85	0.73	0.70	0.99
Skewness	4.98	3.56	2.62	3.59	1.89	3.39	1.99	3.62	3.65	3.88	3.83	4.98
Kurtosis	43.16	30.61	24.66	28.68	19.74	22.77	6.30	17.70	30.72	32.39	34.67	47.96

Notes: In this table, we provide information on the Tobin's Q (defined as (AT+(PRCC·CSHO)-CEQ)/AT, where PRCC is the Annual Price Close (fiscal year end), CSHO is Common Shares Outstanding, AT is Total Assets and CEQ is Common Equity, all in million US$) on our total sample, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available), dividing between small and large firms. The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.23: Data description: Log of TFP - Small and Large firms

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Small						
25%	-0.75	-0.68	-0.48	-0.78	-0.45	-0.80	-0.27	-0.27	-0.78	-0.51	-0.67	-0.72
Median	-0.27	-0.25	-0.01	-0.30	0.00	-0.31	-0.10	-0.10	-0.24	-0.09	-0.25	-0.24
75%	0.31	0.29	0.57	0.24	0.52	0.16	-0.01	0.01	0.27	0.71	0.46	0.31
Mean	-0.21	-0.21	-0.01	-0.25	-0.02	-0.29	-0.16	-0.15	-0.21	0.02	-0.14	-0.21
Std. Dev.	0.88	0.77	0.75	0.85	0.72	0.82	0.46	0.45	0.75	0.80	0.94	0.84
Skewness	0.17	0.02	-0.18	0.17	-0.43	0.16	-0.03	-0.05	0.06	0.34	0.11	0.13
Kurtosis	3.72	3.66	3.39	3.84	3.29	4.04	7.60	8.02	3.63	3.38	3.32	3.75
						Large						
25%	-0.27	-0.33	-0.34	-0.29	-0.39	-0.34	-0.25	-0.27	-0.31	-0.33	-0.22	-0.29
Median	0.13	0.14	0.15	0.08	0.20	0.06	0.08	-0.22	0.08	0.02	0.19	0.14
75%	0.75	0.69	0.73	0.54	0.78	0.58	0.28	0.19	0.51	0.60	0.69	0.70
Mean	0.22	0.18	0.15	0.20	0.18	0.18	0.06	-0.08	0.18	0.08	0.28	0.23
Std. Dev.	0.84	0.78	0.73	0.77	0.77	0.80	0.47	0.52	0.78	0.64	0.74	0.81
Skewness	0.42	0.26	0.04	0.87	-0.03	0.75	0.68	1.31	0.15	0.27	1.01	0.42
Kurtosis	3.76	3.83	3.47	4.43	3.42	4.00	6.75	8.48	3.86	3.31	4.87	3.91

Notes: In this table, we provide information on the log of TFP (Total Factor Productivity), dividing between small and large firms, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.24: Data description: Log of TFP - Old and Young firms

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Old						
25%	-0.76	-0.64	-0.23	-0.63	-0.23	-0.72	-0.43	-0.43	-0.64	-0.75	-0.36	-0.72
Median	-0.27	-0.23	0.19	-0.13	0.24	-0.24	-0.18	-0.18	-0.27	-0.75	0.06	-0.25
75%	0.30	0.27	0.78	0.36	0.78	0.26	0.24	0.24	0.23	-0.72	0.51	0.30
Mean	-0.20	-0.14	0.23	-0.06	0.24	-0.16	-0.20	-0.20	-0.18	-0.67	0.10	-0.18
Std. Dev.	0.91	0.80	0.52	0.86	0.52	0.85	0.54	0.54	0.78	0.17	0.84	0.89
Skewness	0.25	0.54	-0.39	0.60	-0.40	0.82	-0.50	-0.50	0.48	1.77	0.28	0.28
Kurtosis	3.78	4.16	1.94	4.35	1.96	4.61	2.25	2.25	3.97	4.17	4.50	3.88
						Young						
25%	-0.27	-0.33	-0.34	-0.29	-0.39	-0.34	-0.25	-0.27	-0.31	-0.33	-0.22	-0.29
Median	0.13	0.14	0.15	0.08	0.20	0.06	0.08	-0.22	0.08	0.02	0.19	0.14
75%	0.75	0.69	0.73	0.54	0.78	0.58	0.28	0.19	0.51	0.60	0.69	0.70
Mean	0.22	0.18	0.15	0.20	0.18	0.18	0.06	-0.08	0.18	0.08	0.28	0.23
Std. Dev.	0.84	0.78	0.73	0.77	0.77	0.80	0.47	0.52	0.78	0.64	0.74	0.81
Skewness	0.42	0.26	0.04	0.87	-0.03	0.75	0.68	1.31	0.15	0.27	1.01	0.42
Kurtosis	3.76	3.83	3.47	4.43	3.42	4.00	6.75	8.48	3.86	3.31	4.87	3.91

Notes: In this table, we provide information on the log of TFP (Total Factor Productivity), dividing between old and young firms, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.25: Data description: Log of Short-term Debt - Old and Young firms

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Old						
25%	0.55	0.99	2.59	0.94	2.60	0.50	0.17	0.17	1.16	2.59	1.96	0.69
Median	2.19	2.56	3.58	2.70	3.58	1.99	0.36	0.36	2.56	2.62	3.79	2.35
75%	4.05	4.38	3.95	4.85	3.58	4.49	0.92	0.92	4.54	2.62	5.87	4.25
Mean	2.36	2.59	2.98	2.81	2.99	2.25	0.49	0.49	2.71	2.58	3.82	2.47
Std. Dev.	2.73	2.41	2.50	2.66	2.51	2.47	0.57	0.57	2.35	0.06	2.68	2.68
Skewness	0.30	-0.20	-0.53	-0.17	-0.53	-0.18	0.09	0.09	-0.15	-1.66	-0.43	0.19
Kurtosis	3.50	2.65	2.42	2.81	2.40	2.71	1.61	1.61	2.65	3.94	3.22	3.32
						Young						
25%	1.25	1.15	1.53	1.68	1.59	1.03	-0.13	-0.17	1.10	1.31	3.14	1.27
Median	3.25	3.08	3.26	4.13	3.22	3.24	3.05	1.00	2.97	3.69	5.15	3.27
75%	5.37	4.82	4.90	5.97	4.82	5.45	4.89	4.16	4.72	5.10	6.39	5.30
Mean	3.27	2.95	3.17	3.71	3.08	3.11	2.83	1.93	2.87	3.32	4.51	3.22
Std. Dev.	2.90	2.58	2.46	2.73	2.38	2.73	2.77	2.44	2.56	2.65	2.51	2.76
Skewness	-0.01	-0.20	-0.23	-0.53	-0.31	-0.21	0.10	0.51	-0.18	-0.08	-1.07	-0.12
Kurtosis	2.88	2.56	2.70	2.60	2.77	2.36	1.63	2.04	2.57	2.48	3.92	2.77

Notes: In this table, we provide information on the log of short-term debt (code DLC, in million US$) on our total sample, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available), dividing between old and young firms. The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Table 3.26: Data description: Tobin's Q - Old and Young firms

	None/Miss	IC	DE	LEV	IC+DE	IC+LEV	DE+LEV	IC+DE+LEV	IC only	DE only	LEV only	Total
						Old						
25%	1.06	1.11	2.08	1.06	2.08	1.04	2.27	2.27	1.18	1.26	1.16	1.08
Median	1.30	1.34	2.18	1.32	2.18	1.29	3.34	3.34	1.34	1.26	1.31	1.32
75%	1.78	1.91	2.28	1.73	2.28	1.73	4.30	4.30	1.81	1.33	1.68	1.80
Mean	1.66	1.65	2.09	1.63	2.10	1.63	3.41	3.41	1.62	1.31	1.62	1.66
Std. Dev.	1.27	1.09	0.62	1.13	0.62	1.16	1.18	1.18	1.09	0.09	1.08	1.23
Skewness	6.32	9.77	0.66	4.60	0.62	4.34	0.29	0.29	13.45	1.48	5.11	6.82
Kurtosis	78.66	224.21	7.18	33.72	7.29	29.85	1.84	1.84	351.80	3.52	42.02	97.47
						Young						
25%	1.11	1.13	1.18	1.08	1.20	1.08	1.08	1.03	1.16	1.15	1.10	1.12
Median	1.45	1.44	1.51	1.29	1.51	1.28	1.40	1.26	1.48	1.50	1.30	1.43
75%	2.07	1.99	2.04	1.68	2.04	1.64	2.06	2.19	2.04	1.98	1.72	2.01
Mean	1.89	1.75	1.75	1.56	1.73	1.53	1.68	1.57	1.84	1.79	1.61	1.81
Std. Dev.	1.69	1.14	1.02	0.96	0.98	0.93	0.78	0.67	1.22	1.12	1.01	1.44
Skewness	12.97	6.30	4.67	10.79	4.11	13.95	1.45	0.98	5.32	5.70	7.47	12.12
Kurtosis	497.93	161.45	44.05	379.74	28.54	615.97	5.34	3.64	117.88	68.23	147.39	506.89

Notes: In this table, we provide information on the Tobin's Q (defined as (AT+(PRCC·CSHO)-CEQ)/AT, where PRCC is the Annual Price Close (fiscal year end), CSHO is Common Shares Outstanding, AT is Total Assets and CEQ is Common Equity, all in million US$) on our total sample, for the different covenants: Interest Coverage (IC), Debt-to-EBITDA (DE), Leverage (LEV), and None/Missing (where information for the covenants is not available), dividing between old and young firms. The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

Figure 3.3: Net Borrowing with short-term debt for unconstrained firms

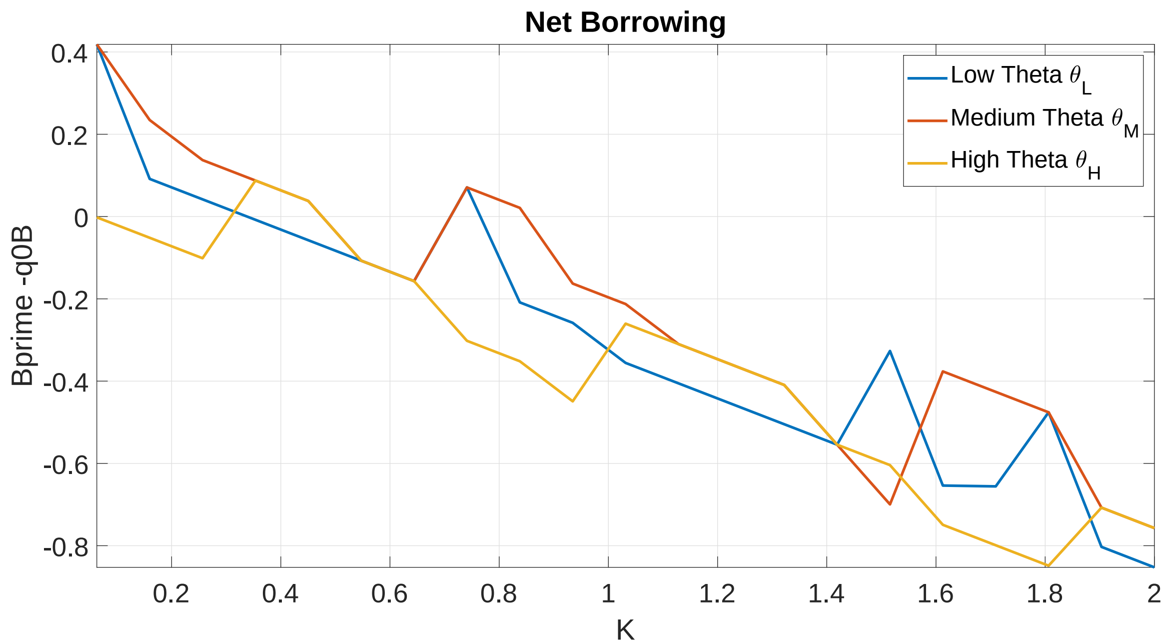


Figure 3.4: Net Borrowing with short-term debt for earnings-based constrained firms

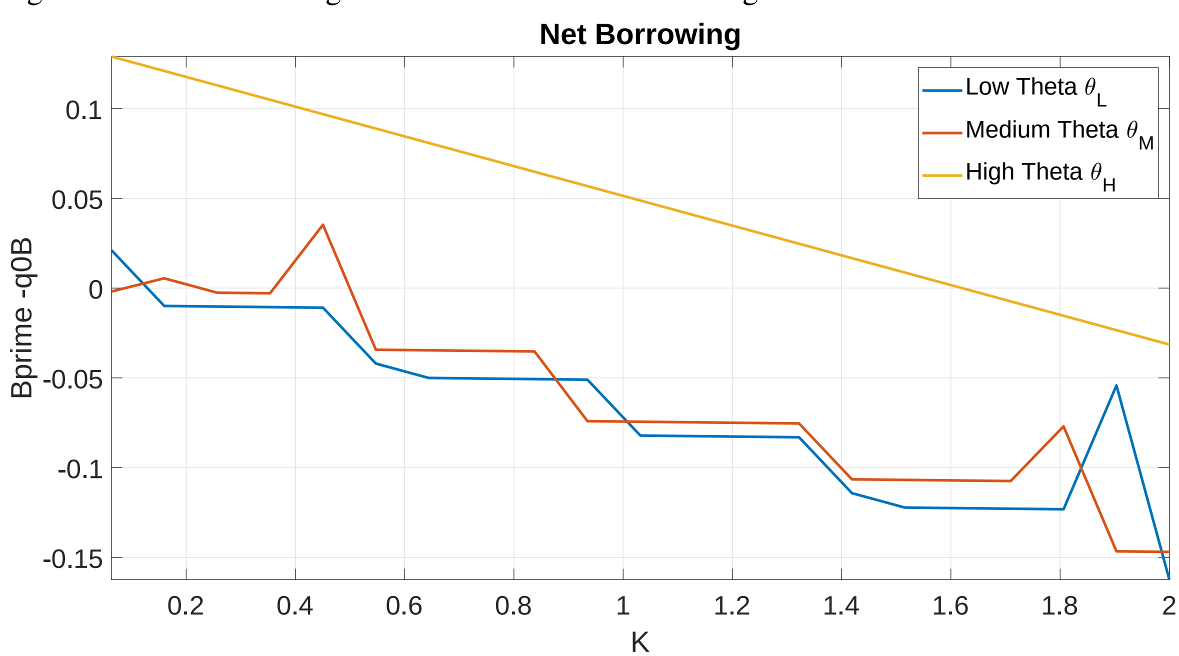


Figure 3.5: Net Borrowing with short-term debt for asset based constrained firms

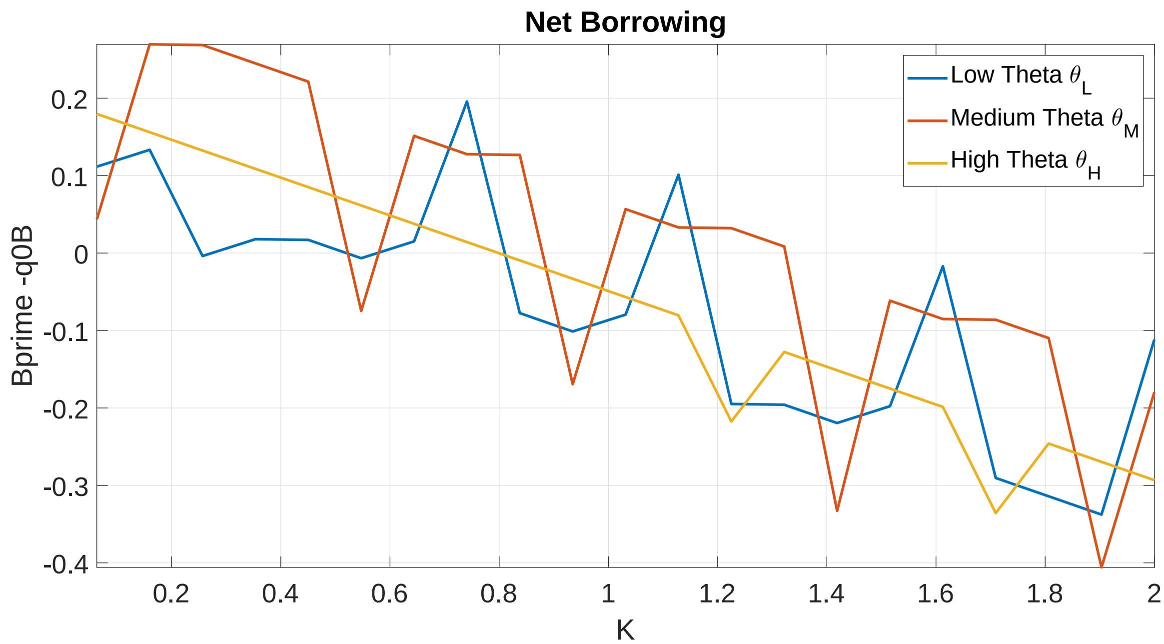


Figure 3.6: Optimal labor with short-term debt

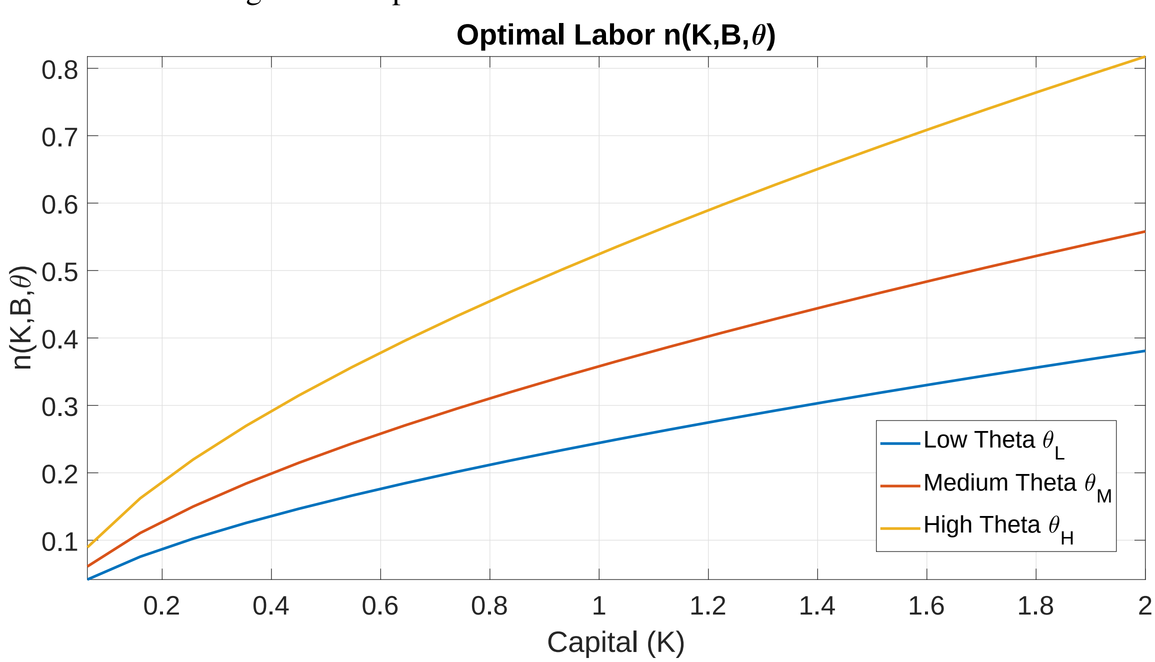


Figure 3.7: Optimal investment with short-term debt

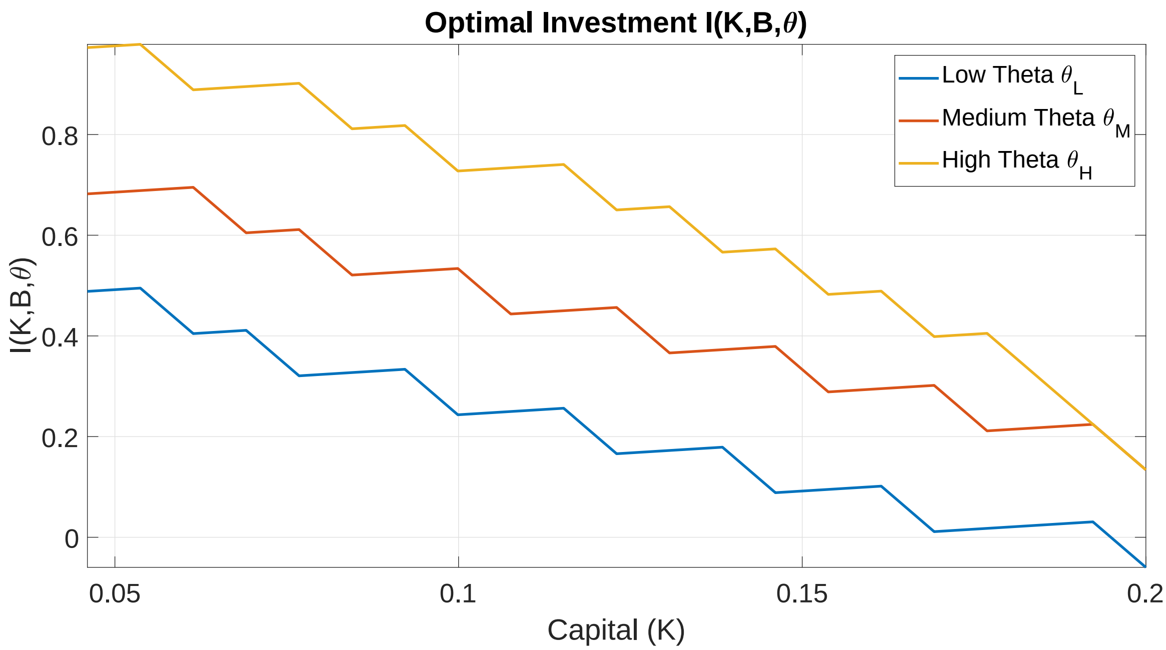


Figure 3.8: Optimal Value Function with short-term debt

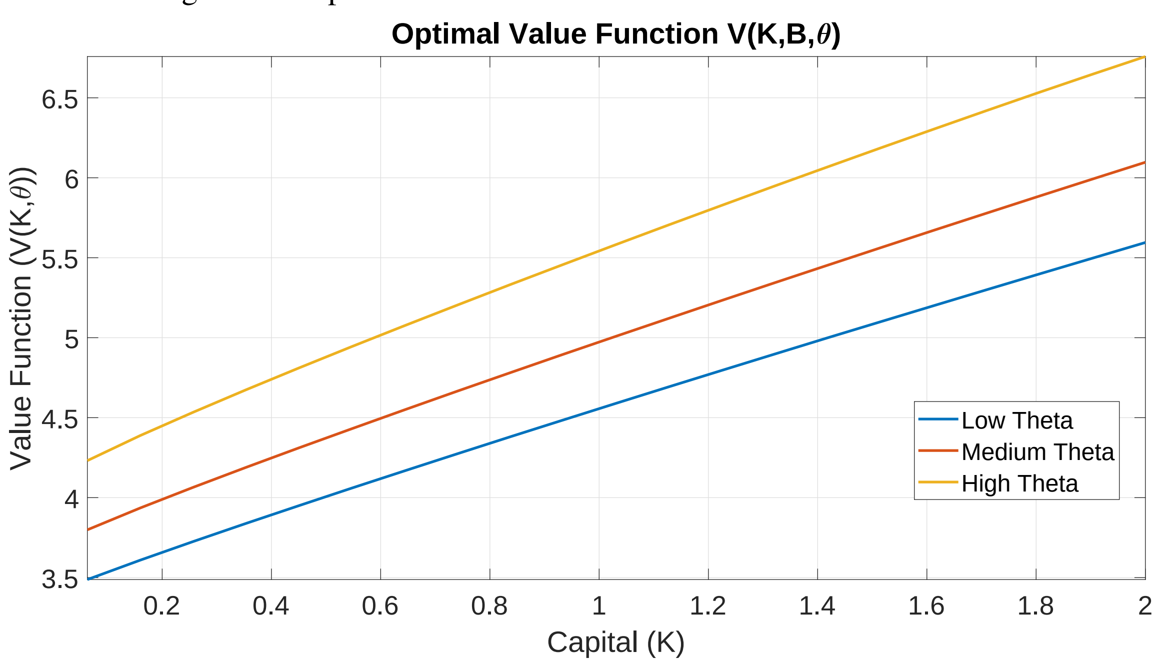


Figure 3.9: Optimal Value Function with short-term debt and earnings-based constraint

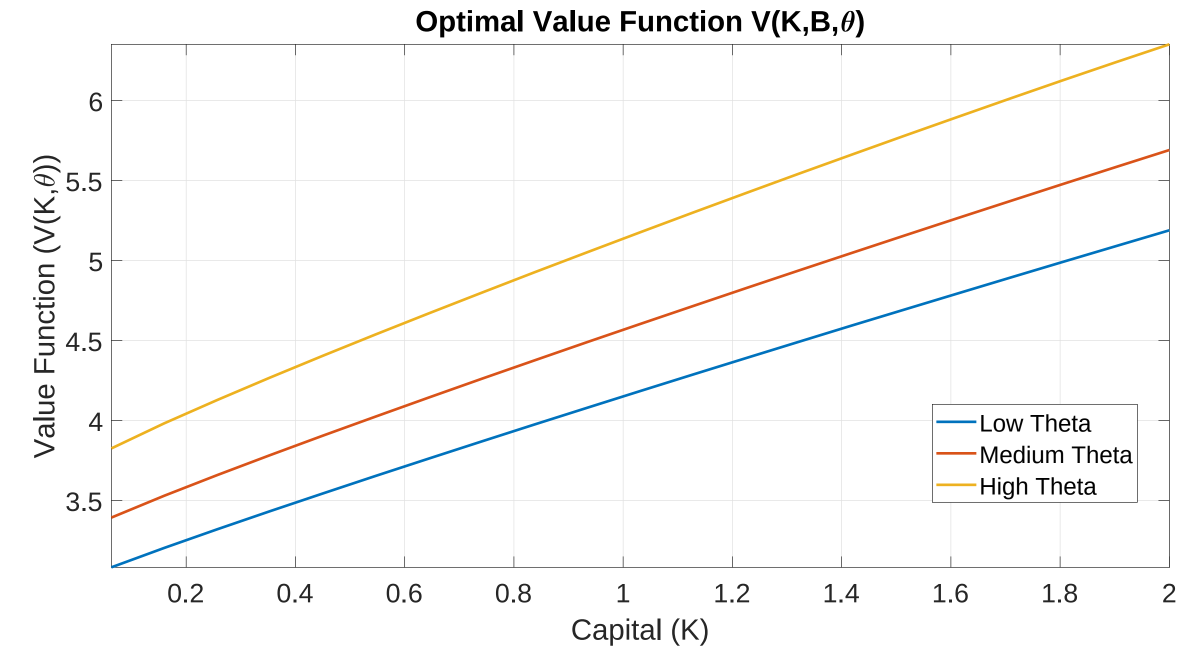


Figure 3.10: Net Borrowing with long-term debt

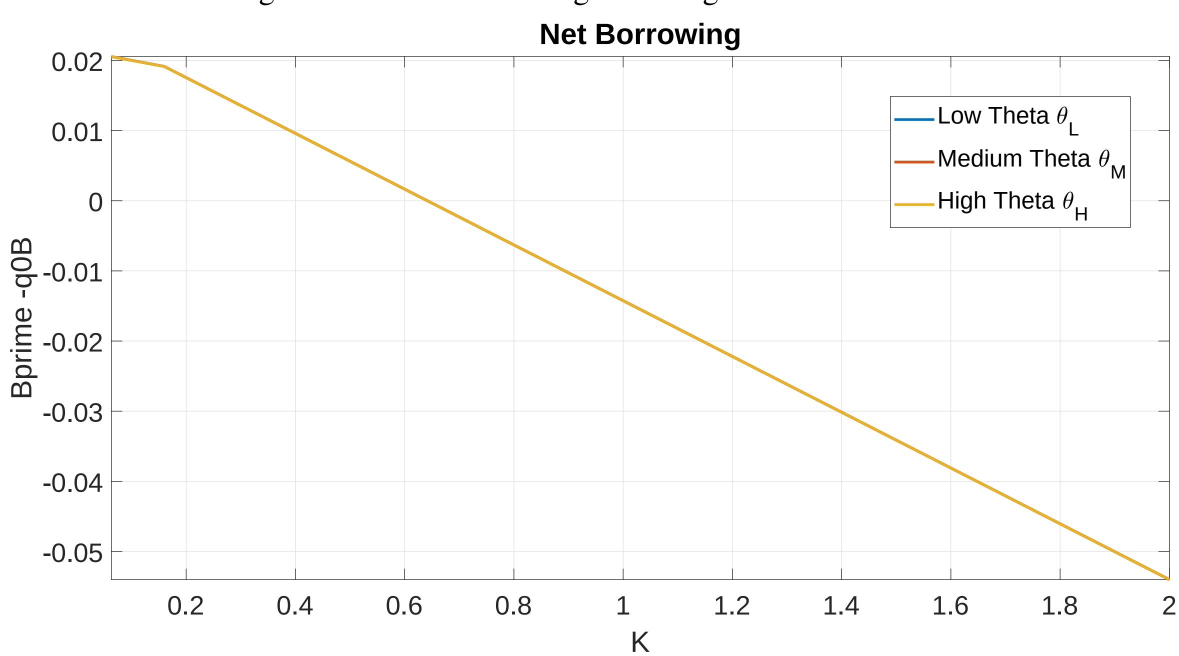


Figure 3.11: Optimal Value Function with long-term debt

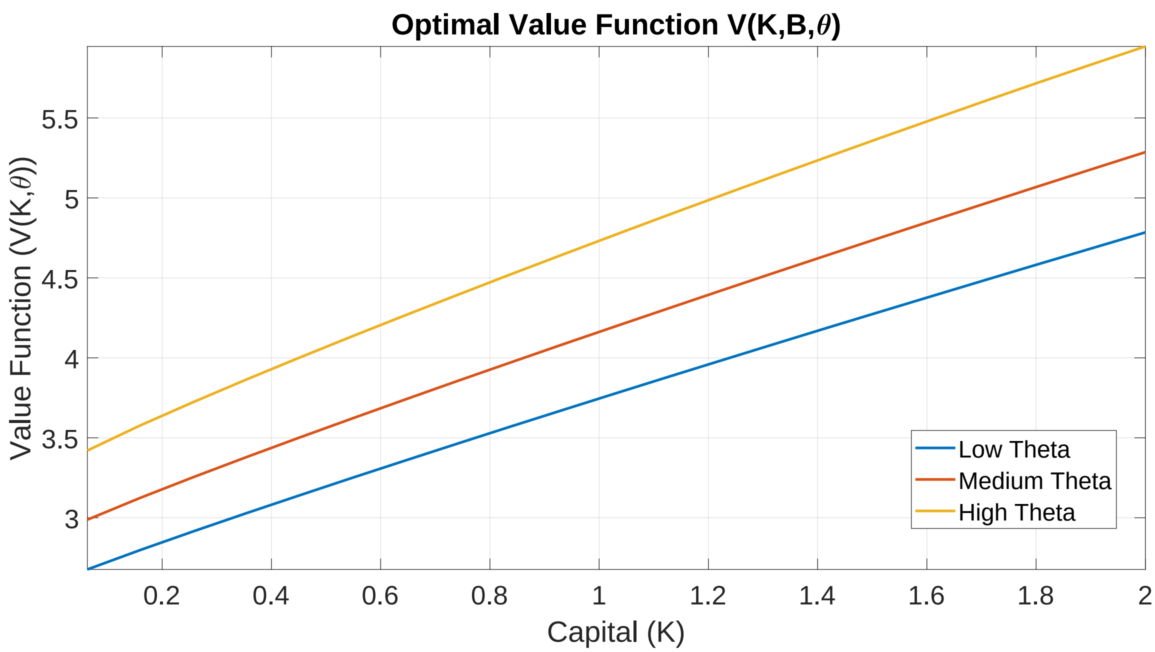


Table 3.27: Simulation Results

	None	IC	LEV	None	IC	LEV	None	IC	LEV	None	IC	LEV	None	IC	LEV
	Short-term debt			Long-term debt			Employment			Capital			Investment		
25%	0.28	0.06	0.23	0.04	0.04	0.04	0.52	0.52	0.52	1.90	1.90	1.90	0.13	0.13	0.13
Median	0.30	0.06	0.30	0.05	0.05	0.05	0.56	0.56	0.56	1.95	1.95	1.95	0.15	0.15	0.15
75%	0.32	0.09	0.34	0.05	0.05	0.05	0.57	0.56	0.56	2.00	2.00	2.00	0.17	0.17	0.17
Mean	0.30	0.08	0.29	0.05	0.05	0.05	0.56	0.56	0.56	1.95	1.95	1.91	0.15	0.14	0.14
Std. Dev.	0.08	0.05	0.08	0.01	0.01	0.01	0.15	0.15	0.15	0.18	0.18	0.18	0.12	0.12	0.12
Skewness	0.44	1.22	-0.83	-9.85	-9.85	-9.85	0.07	0.08	0.07	-2.20	-2.06	-2.14	0.12	4.15	0.12
Kurtosis	4.56	2.65	2.78	98.02	98.02	98.02	3.20	3.10	3.15	8.14	7.41	7.84	29.77	28.95	29.20

Notes: In this table, we provide information on the simulated variables, to compare with our empirical data, for the different scenarios: earnings based constraint (IC), asset based constraint (LEV), and unconstrained (None)). The indicators on the left column include the 25%, 50% (median), and 75% percentiles, the mean, standard deviation, skewness and kurtosis.

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