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Essays on Commodity Dependence, Economic Performance, and Credit Risks

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Abstract

This thesis comprises three chapters, each belonging to different strands of the empirical macro-finance literature.

The first essay (Chapter 2) investigates how shocks to global economic activity, financial conditions, and commodity prices influence macroeconomic and stock market performance in commodity-export-dependent countries. We focus on eight countries, including four developed economies (Australia, Canada, New Zealand, and Norway) and four emerging economies (Brazil, Chile, Russia, and South Africa). Methodologically, we utilise country-specific structural vector autoregressions (SVARs) and identify three shocks: global activity, global financial risk, and commodity-specific price shocks. We find that global activity shocks have statistically significant expansionary effects on real GDP across the sampled countries, except for New Zealand. These shocks cause a statistically significant short-term rise in the stock markets of Australia, Canada, Norway, and South Africa. The effect is weakly significant for Brazil and Russia, and insignificant for Chile and New Zealand. Global financial risk shocks generally have no significant contractionary effect on real GDP in most countries. However, these shocks lead to statistically significant declines in stock markets across all countries, with Russia and Brazil suffering the largest falls. Commodity-specific price shocks have limited impact on output in most sampled countries, while their positive influence on stock markets is only briefly significant after the initial impact.

The second essay (Chapter 3) examines the influence of macroeconomic risks on overall investment-grade corporate credit spreads in the U.S. using monthly data from August 1987 to December 2019. We analyse the yield spreads between AAA-rated bonds and 20-year Treasury bonds, as well as BAA-rated bonds and 20-year Treasury bonds. Using quantile regressions, we develop three risk measures related to industrial production growth: growth-at-risk (a measure of downside risk), uncertainty, and skewness (a measure of the balance between downside and upside risks). Results show that our novel risk measures provide significant explanatory power beyond the traditional factors recognised in existing research. We find that increases in growth-at-risk and uncertainty significantly widen corporate credit spreads, whereas increases in skewness have a statistically significant

narrowing effect. The BAA-Treasury credit spread exhibits the greatest sensitivity to macroeconomic risks. A principal component derived from these three risk measures, obtained via principal component analysis (PCA), significantly widens the aggregate corporate credit spreads, offering additional explanatory power greater than that of the individual risk measures.

Finally, the third essay (Chapter 4) examines whether the impact of global commodity prices on sovereign CDS spreads in commodity-export-dependent developed countries (Australia and Norway) and emerging economies (Brazil and Russia) is regime-dependent. Using weekly data from December 2008 to February 2022, we identify tranquil and turbulent regimes using Markov-switching regressions. We find that commodity price changes significantly lower sovereign CDS spreads in Australia, Brazil, and Russia during both regimes, but only during turbulent periods for Norway's CDS spreads. Across all countries, the effect during crises is larger than during tranquil periods. The influence of commodity prices is strongest on Russia's CDS spreads, while Norway shows the least sensitivity across regimes. In addition to confirming our initial findings, time-varying transition-probability Markov-switching regressions reveal that increased global financial stress raises the likelihood of switching to high-volatility regimes for the CDS spreads of Australia, Brazil, and Russia. Results also indicate that commodity price changes increase the likelihood of remaining in a low-volatility sovereign CDS regime in Norway, but tend to raise the probability of switching to a crisis regime in Russia.

Table of Contents

Abstract i

List of Tables vi

List of Figures viii

1 Introduction 1

1.1 Chapter 2: Background, contributions, and findings 1

1.2 Chapter 3: Background, contributions, and findings 4

1.3 Chapter 4: Background, contributions, and findings 6

References 9

2 Macroeconomic and Stock Market Performance in Commodity-exporting Economies 13

2.1 Introduction 13

2.2 Relationship with the Literature and Hypothesis Development 19

2.2.1 Theoretical underpinnings 19

2.2.2 Commodity prices and global macroeconomic factors 20

2.2.3 Global shocks and real activity 22

2.2.4 Global shocks and stock market performance 23

2.2.5 Hypothesis development 25

2.3 Data overview 26

2.3.1 Country characteristics 26

2.3.2 Sample period and frequency 26

2.3.3 Variables 26

2.4 Empirical Framework 29

2.4.1 Specifying the Structural Vector Autoregressions 29

2.4.2 Estimation 36

2.4.3 Inference 37

2.4.4 Model adequacy 37

2.5 Main Results 39

2.5.1 Global variables 39

2.5.2 The effects of global shocks on real GDP 41

2.5.3 The effects of global shocks on equity markets 44

2.6 Sensitivity analysis 47
2.6.1 Robustness to an alternative measure of output 47
2.6.2 Robustness to an alternative measure of global financial risk 48
2.6.3 Subsample analysis: 2003 to 2019 period 49
2.6.4 Robustness to detrending 50
2.6.5 Robustness to data frequency 51
2.7 Concluding remarks 52
2.8 Tables and Figures 55
2.8.1 Tables 55
2.8.2 Figures 71
2.9 Appendix A 87
References 95
3 Economic Growth Risks and Corporate Credit Spreads 102
3.1 Introduction 102
3.2 Theoretical background, related literature, and hypothesis development 108
3.2.1 Theoretical background 108
3.2.2 Related literature 110
3.3 Data and methodology 114
3.3.1 Variable construction 114
3.3.2 Dependent variables 118
3.3.3 Control variables 118
3.3.4 Descriptive statistics 120
3.4 Empirical results 122
3.4.1 Empirical methodology 122
3.4.2 Robustness checks 126
3.4.3 Additional tests 130
3.4.4 Discussion and Implications 133
3.5 Conclusion 135
3.6 Figures and tables 138
3.6.1 Tables 138
3.6.2 Figures 150
3.7 Appendix B 154
References 163

4 Sovereign credit default swaps in commodity-exporting countries....170
4.1 Introduction....170
4.2 Country characteristics, theoretical background, and literature review....175
4.2.1 Country characteristics....175
4.2.2 Theoretical background....178
4.2.3 Literature review....179
4.3 Econometric methodology....185
4.3.1 Markov-switching Dynamic Regression Model....185
4.4 Data....187
4.4.1 The dependent variable: the sovereign CDS spread....187
4.4.2 Global Commodity Price Changes....187
4.4.3 Control variables....188
4.4.4 Preliminary data analyses....189
4.5 Empirical results and discussion....191
4.5.1 OLS regression analysis....191
4.5.2 The constant transition probability Markov-switching model....193
4.5.3 Robustness checks....197
4.5.4 Economic Implications....204
4.6 Conclusion....206
4.7 Tables and figures....209
4.7.1 Tables....209
4.7.2 Figures....222
4.8 Appendix C....224
References....228
5 Conclusion....236
5.1 Key Findings, implications, and future research....236
References....240

List of Tables

Table 2.1 Commodity exports as a share of merchandise exports and GDP (2012–14).....55
Table 2.2 Data description and sources.....55
Table 2.3a SVAR Dummy Variables.....56
Table 2.4 CXPI Forecast error variance decompositions.....58
Table 2.5 Real GDP Forecast error variance decompositions.....59
Table 2.6 Stock market index forecast error variance decompositions.....60
Table 2.7 Industrial Production Index FEVDs [Robustness - Industrial Production Index]61
Table 2.8 Stock Market FEVD [Robustness - Industrial Production Index].....62
Table 2.9 Real GDP FEVDs [Robustness - VIX].....63
Table 2.10 Stock Market FEVDs [Robustness - VIX].....64
Table 2.11 Real GDP FEVDs [Robustness: 2003-2019 period].....65
Table 2.12 Stock Market FEVDs [Robustness: 2003-2019 period].....66
Table 2.13 Real GDP FEVDs [Robustness - non-detrended data].....67
Table 2.14 Stock Market Index FEVDs [Robustness - non-detrended data].....68
Table 2.15 Real GDP FEVDs [Robustness - Quarterly Data].....69
Table 2.16 Stock Market FEVDs [Robustness - Quarterly Data].....70
Table 3.1 Data description and sources.....138
Table 3.2 Accuracy of the conditional quantiles.....139
Table 3.3 Summary statistics.....139
Table 3.4 OLS regression estimates.....140
Table 3.5 The long-term effects of the output growth proxies.....141
Table 3.6 GMM regressions.....142
Table 3.7 OLS regression estimates - Option adjusted spreads (OAS).....143
Table 3.8 ARMA-GJR-GARCH model.....144
Table 3.9 GARCH-based Growth-at-Risk and Uncertainty measures.....145
Table 3.10 Quantile regression estimates [Growth-at-Risk].....146
Table 3.11 Quantile regression estimates [Uncertainty].....147
Table 3.12 Quantile regression estimates [SKEW].....148
Table 3.13 OLS regression estimates with principal component.....149
Table 4.1 Data description and sources.....209
Table 4.2 Descriptive Statistics.....210
Table 4.3 Correlation between the local and global variables.....210

Table 4.4 Linear models estimation of sovereign CDS spreads.....211
Table 4.5a Markov-Switching model results 212
Table 4.6 Tests for coefficient equality between states for FTP model estimates.....214
Table 4.7a TVTP Markov-Switching model results.....215
Table 4.8 Tests for coefficient equality between states for TVTP model estimates.....217
Table 4.9a Quantile regression estimates 218
Table 4.10a Markov-Switching model results [Alternative commodity price index].....220

List of Figures

Figure 2.1 Global variables' impulse responses to global shocks.....71
Figure 2.2 CXPI responses to one-standard-deviation shocks to the global variables 72
Figure 2.3 Real GDP responses to the global shocks.....73
Figure 2.4 Stock market responses to the global shocks.....74
Figure 2.5 Averaged percentage contributions of global shocks.....75
Figure 2.6 Industrial production index responses to the global shocks [Robustness] 76
Figure 2.7 Stock market responses to global shocks [Robustness - IPI] 77
Figure 2.8 Real GDP response to the global shocks [Robustness - VIX].....78
Figure 2.9 Stock market response to the global shocks [Robustness - VIX].....79
Figure 2.10 Real GDP response to global shocks [Robustness: 2003-2019 sample] 80
Figure 2.11 Stock market responses to global shocks [Robustness: 2003-2019 sample]....81
Figure 2.12 Real GDP responses to global shocks [Robustness - non-detrended] 82
Figure 2.13 Stock market responses to global shocks [Robustness - non-detrended] 83
Figure 2.14 Real GDP response to global shocks [Robustness - Quarterly data].....84
Figure 2.15 Stock market response to the global shocks [Robustness - Quarterly data].....85
Figure 2.16 Robustness of stock market responses to global shocks.....86
Figure 3.1 Corporate credit spreads 150
Figure 3.2 IP growth risk measures.....151
Figure 3.3 Scree Plot (Ordered Eigenvalues).....152
Figure 3.4 Orthonormal Loadings.....152
Figure 3.5 Time series of the first principal component 153
Figure 4.1 Time series plots of the sovereign CDS spreads.....222
Figure 4.2 FTP smoothed probabilities of the crisis state.....222
Figure 4.3 TVTP smoothed probabilities of the crisis state.....223

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Author’s Declaration

I declare that, except where explicit reference is made to the contribution of others, this dissertation 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.

Printed name: Brian Madzivanyika

Signature

1 Introduction

The dissertation includes three chapters. The first examines how global shocks affect macroeconomic and stock market performance in advanced and emerging commodity-exporting countries. The second chapter investigates whether macroeconomic downside risk, uncertainty, and skewness can explain aggregate corporate credit spreads in the U.S. Lastly, the third chapter examines the regime-dependent impact of commodity price changes on sovereign credit default swap spreads across four developed and emerging countries that are dependent on commodity exports.

This introductory chapter provides a brief overview of the background and motivations for each chapter. It also discusses the research questions, methodological approaches, contributions, and key findings for each chapter.

1.1 Chapter 2: Background, contributions, and findings

The chapter explores the effects of shocks to global economic activity, global financial conditions, and commodity prices on the economic and stock market performance of countries heavily reliant on commodity exports. Aggregate fluctuations in these countries often follow the booms and busts of commodity prices, presenting considerable challenges for policymakers.

UNCTAD (2019) notes that between 2013 and 2017, more than half of the world's economies relied heavily on commodity export revenues. While countries dependent on commodity exports are mainly low-income, least developed nations, some emerging economies and developed countries also fall into this category. However, academic research rarely explores the impact of commodity prices on developed economies that depend on commodity exports. This chapter examines eight commodity-exporting countries, including four developed economies (Australia, Canada, New Zealand, and Norway) and four emerging economies (Brazil, Chile, Russia, and South Africa).

Relying on primary commodity exports exposes exporters to various global shocks that cause fluctuations in commodity prices (Kilian 2009; Juvenal and Petrella 2024). Commodity price fluctuations, therefore, act as channels for transmitting global shocks that impact domestic macroeconomic aggregates and asset prices in different ways. Recent studies show that shocks to aggregate commodity demand have a much greater effect on

fluctuations in real commodity prices than supply shocks (Kilian, 2009; Jack and Stuermer, 2020). The International Monetary Fund (IMF, 2012) finds that unexpected changes in global economic activity, which lead to shifts in commodity prices, notably influence exporters' real activities, while unanticipated variations in global commodity production usually have limited effects. Global financial conditions can also significantly impact supply and demand in commodity markets through various channels. Frankel (2008) emphasises the role of interest rates in affecting production and demand for inventories.

There is a lively debate about how commodity prices and terms of trade influence business cycles. Research by Mendoza (1995) and Kose (2002) indicates that changes in terms of trade largely drive fluctuations in macroeconomic aggregates, while studies including Schmitt-Grohe and Uribe (2018), Fernández et al. (2017), and Drechsel and Tenreyro (2018) suggest that global shocks such as commodity prices and interest rates significantly contribute to explaining variations in output and other indicators of aggregate activity.

An emerging body of literature highlights policymakers' concerns regarding the potential impacts of the global financial cycle on domestic economic performance (Rey, 2015; Habib and Venditti, 2018). Key factors influencing the global financial cycle include global risk aversion and US monetary policy, which significantly drive capital flows and asset returns. Recent studies, including Akyüz (2022) and Juvenal and Petrella (2024), emphasise the relationships between global activity, financial conditions, and commodity prices, highlighting their significant influence on growth in commodity-dependent economies.

The impact of commodity market shocks on stock prices has important implications for both investors and policymakers. Policymakers pay close attention to stock market fluctuations, as these can greatly influence households' consumption and savings decisions (Cieslak and Vissing-Jorgensen, 2021). Changes in household wealth are considered a key factor driving fluctuations in economic activity. However, empirical research on commodity prices and stock markets primarily focuses on the effects of oil shocks on the U.S., oil-importing developed economies, or oil exporters.

The chapter methodologically relies on country-specific structural vector autoregression (SVAR) models. It identifies three types of shocks: a global activity shock, a global financial risk shock, and a commodity (specific) price shock. The aim is to explore how global economic activity, financial risks, and commodity prices affect output and stock

markets in economies dependent on commodity exports. Additionally, it examines which global shocks have the greatest impact on stock markets and economic performance. It also assesses whether there are notable differences in responses to these shocks between emerging and developed economies.

This chapter contributes to empirical research in several ways. Firstly, it investigates how global shocks affect total economic output and stock market performance in commodity-exporting countries. Some of the advanced economies included are seldom analysed in previous research. Second, it compares the dynamic responses of these variables to global shocks between developed and emerging commodity-exporting economies. Prior research on oil shocks has primarily concentrated on the relationship between commodity prices and the macroeconomy in the US and other oil-importing advanced nations. Third, it enriches the existing literature on the link between commodity export prices and stock markets, which, to date, has mainly focused on the relationship between oil prices and stock markets.

The estimated impulse response functions indicate that the global activity shock temporarily eases global financial conditions and increases country-specific commodity export price indices (CXPIs) across all countries. This shock has statistically significant expansionary effects on output across the sampled countries, with the notable exception of New Zealand. The expansionary impact on real GDP appears more pronounced in emerging economies, especially Russia, followed by Brazil. The stock markets in Australia, Canada, Norway, South Africa, and, to some extent, Brazil, exhibit a statistically significant positive response to the shock.

We find that a deterioration in global financial conditions causes a sharp reduction in global economic activity and an immediate, statistically significant decline in the CXPIs. While this shock generally does not lead to statistically significant contractions in real GDP in most countries, it does cause statistically significant negative responses in stock markets across all sampled countries, with Russia and Brazil experiencing the largest declines. Commodity-specific price shocks have little effect on global economic activity and financial conditions. The shock has a negligible impact on output across most sampled countries. Its effect on equity markets in most countries is minor, triggering a briefly statistically significant positive response.

Forecast error variance decompositions indicate that the global activity shock is the most influential external shock affecting output fluctuations, with a stronger impact in

emerging market economies (EMEs). In contrast, global financial risk and commodity-specific price shocks are generally less relevant for variations in output across the sampled countries. On average, external shocks contribute a larger share to output fluctuations in emerging economies than in developed economies.

Stock market forecast error variance decompositions indicate that the global financial risk shock is the most significant external shock, particularly for Australia, Brazil, Canada, Chile, and Norway. The global activity shock contributes relatively modestly to stock market volatility in advanced economies, while accounting for a smaller share of variation in emerging economies. Global shocks generally have a more pronounced impact on stock market fluctuations in developed economies than in emerging economies, especially over short- to medium-term forecast horizons.

1.2 Chapter 3: Background, contributions, and findings

The objective of the third chapter is to assess the quantitative importance of output growth risk for explaining investment-grade corporate credit spread dynamics in the U.S. There has been a resurgence of interest in the hypothesis that macroeconomic risks are a major determinant of economic and financial outcomes.

The total amount of outstanding US corporate debt relative to GDP has increased in recent years, especially after the 2008 financial crisis and during the COVID-19 pandemic. Of particular concern to policymakers and analysts is the investment-grade sector, which has become much riskier as it is now largely composed of bonds issued by BBB-rated companies. These BBB bonds face the risk of being downgraded to high-yield status, known as falling angels. This risk becomes more pronounced during economic downturns, potentially raising borrowing costs for issuers and leading to declines in investment, employment, and sales growth. Additionally, forced sales by institutional investors can push bond prices below their fundamental values, weakening banks' and insurers' balance sheets. Overall, this heightens concerns about financial stability and its potential repercussions for the broader economy.

Our analysis is also driven by a long-standing question about the factors that influence the dynamics of corporate credit spreads. Research using the structural approach to credit risk modelling (Black and Scholes, 1973; Merton, 1974) reveals that credit risk accounts for only a small portion of the observed spread in investment-grade bonds across all maturities, a phenomenon known as the credit spread puzzle (Huang and Huang, 2012). Increasingly, recent studies explicitly incorporate the macroeconomic state into Merton's

framework to address the credit spread puzzle (e.g., Chen, 2010; Bhamra et al., 2010). Evidence suggests that investors consider the possibility of severe economic shocks, which affect their risk attitudes. Indeed, empirically, corporate credit spreads are strongly countercyclical (Fama and French, 1989), widening during periods of significant economic downturns, such as financial crises and recessions, and narrowing during periods of economic expansion.

Therefore, the macro-finance literature contends that macroeconomic tail risks are crucial for understanding asset prices. Studies including Gourio (2013), Gabaix (2012) and Marfe and Pénasse (2024) suggest that reconciling asset prices and macroeconomic risk quantitatively helps to solve many puzzles in macro-finance.

We draw on the macroeconomic literature, which emphasises that a more precise assessment of macroeconomic risks and their potential effects on the economy is essential for policy analysis and risk management. Policymakers and market participants are concerned not only about uncertainty in economic growth but also about tail risks. In line with Ghysels et al. (2018) and Castelnuovo and Mori (2025), we develop monthly measures of uncertainty, downside tail risk, and skewness using the quantile regression approach. We utilise the U.S. industrial production index as an indicator of overall economic activity in the United States. We derive the IP growth-at-risk measure as a proxy for macroeconomic downside risk. We estimate the inter-quantile ranges as a robust proxy for volatility, which is often used as a proxy for uncertainty. Our third measure of economic risk is skewness, which captures the imbalance between upside and downside risks.

We explore whether risk measures offer additional relevant information for determining corporate credit spreads beyond the factors identified in existing literature. The research questions are: Do second and higher moments in U.S. output growth explain aggregate U.S. corporate credit spreads? Do they have incremental explanatory power beyond the traditional determinants of credit spreads identified in the literature?

Methodologically, we initially employ ordinary least squares (OLS) estimation as our baseline. For robustness checks, we use a generalised method of moments (GMM) model with instrumental variables to address potential endogeneity, and a quantile regression model to examine non-linearity in the relationship. Additionally, we construct Growth-at-Risk and uncertainty measures using the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model to verify robustness.

Our research contributes to several strands of literature. Firstly, we address the body of work on the determinants of credit spreads by examining the effects of macroeconomic conditions. We consider Moody's Seasoned Aaa and Baa Corporate Bond Yield spreads relative to the yield on the 20-Year Treasury Constant Maturity. Secondly, we contribute to the rapidly expanding area of research investigating the informational content of fundamental second moments (e.g., Baum and Wan, 2010; Bloom, 2014) and higher-order moments of asset prices (Segal et al., 2015; Colacito et al., 2016). Our finding of the significant effects and the additional explanatory power of all three output growth risk proxies for credit spreads, beyond the determinants identified in the literature, represents a novel contribution of this paper.

Our analysis indicates that growth-at-risk and uncertainty risk measures are associated with statistically significant increases in corporate credit spreads. Conversely, higher skewness risk tends to narrow overall credit spreads. The BAA20Y spread reacts more strongly to economic growth risks than the AAA20Y spread. Even after accounting for known factors that influence credit spreads, these risk measures remain highly significant. They provide additional explanatory power beyond traditional indicators such as the first moment of the industrial production index and other recognised credit spread factors. Furthermore, through principal component analysis of the three risk measures, we identify a principal component that significantly widens credit spreads, with explanatory power exceeding that of the individual growth-at-risk, uncertainty, and skewness risk measures.

1.3 Chapter 4: Background, contributions, and findings

Chapter 4 examines the impact of global commodity prices on sovereign credit risk in both advanced (Australia and Norway) and emerging (Brazil and Russia) commodity export-dependent countries. Using sovereign credit default swaps as a measure of sovereign credit risk, we argue that the relationship between the sovereign risk of commodity exporters and changes in commodity prices is regime-dependent.

Between 2008 and 2022, global sovereign debt increased significantly as countries issued more debt to support their economies following the 2007-09 Global Financial Crisis and the COVID-19 pandemic. This expansion was driven by favourable funding conditions characterised by low real interest rates that remained below growth rates (Adrian et al., 2024). Sovereign debt in commodity-exporting, emerging, and developed nations rose sharply from around 33% of GDP in 2010 to approximately 58% in 2022 (World Bank, 2024). Reinhart et al. (2016) emphasise that commodity price cycles have historically been

key drivers of sovereign defaults. Elevated debt levels make these countries vulnerable to sudden drops in commodity prices, which can impede governments' ability to meet current and future repayment obligations. This threatens to worsen debt sustainability, potentially leading to debt distress. Consequently, sovereign yield spreads tend to widen, adversely affecting economic growth.

Eaton and Gersovitz (1981) note that negative shocks—such as declining export prices, economic downturns, or rising debt service costs—can trigger sovereign defaults. The consequences of a sovereign debt crisis include reduced access to future funding, higher borrowing costs, slower economic growth, reputational damage, and increased poverty and social problems (Borensztein and Panizza, 2009; Cruces and Trebesch, 2013). Furthermore, debt distress limits a country's ability to respond to future economic shocks and manage financial stability risks.

The previous research has mostly focused on sovereign debt crises in emerging and developing nations. Historically, advanced countries have been seen as more resilient because of their diverse economies, strong institutional frameworks, higher tax revenues, and greater ability to meet policy objectives (Mitchener and Trebesch, 2023). However, the Global Financial Crisis (GFC) and the subsequent eurozone debt crisis have exposed the vulnerability of some advanced economies to debt crises.

According to Tomz and Wright (2007), sovereign defaults are more common during economic downturns than in prosperous periods. Boehm et al. (2021) analyse the impact of macroeconomic factors on commodity-sovereign risk dependence and find that reliance on commodities for sovereign funding increases during economic recessions (lower GDP growth). Delatte et al. (2017) demonstrate that the pricing of sovereign credit risk varies across regimes. Several empirical research studies investigating the fundamental factors influencing sovereign yield spreads have identified two distinct regimes: low-volatility (crisis) and high-volatility (non-crisis) (e.g., Calice et al., 2015). They report a heightened sensitivity to fundamentals during times of crisis. Blommestein et al. (2016) find that the sovereign CDS market for specific Eurozone nations switches between stable and crisis periods.

Empirically, the chapter employs simple ordinary least squares (OLS), Markov-switching regression with fixed and time-varying transition probabilities, and quantile regressions. The objective is to answer the following research question: Is the impact of commodity price fluctuations on sovereign credit risk in commodity-exporting countries

regime-dependent? Do changes in commodity prices similarly influence fluctuations in sovereign CDS spreads across advanced and emerging economies? Are there observable variables that can assist in predicting transitions between different crisis and tranquil regimes?

We make several significant contributions to the literature on the factors influencing changes in sovereign credit risk. First, we contribute by investigating the nonlinearity in the relationship between sovereign CDS spreads and commodity price fluctuations. Most of the relevant literature relies on single-regime linear regression techniques. Second, we add to the sparse literature examining the sovereign risk of resource-rich countries. Our selected countries include the advanced commodity-export-dependent economies of Australia and Norway, which are rarely the focus of existing studies. Furthermore, the countries differ in the types of commodities they export: Australia mainly exports metals, Brazil primarily exports agricultural commodities, and Norway and Russia primarily export energy. This country-level diversity allows us to compare how sovereign risk across nations responds to fluctuations in commodity prices. Finally, we utilise the Standard & Poor's Goldman Sachs Commodity Index (S&P GSCI) to measure global commodity prices, contrasting this with the substantial empirical literature that concentrates on the impact of oil price shocks.

The chapter finds that fluctuations in global commodity prices are significantly negatively related to sovereign credit risk across both emerging and advanced economies, though with varying magnitudes. Estimation results show that sovereign CDS spreads respond more strongly to changes in global commodity prices during crises than in non-crisis periods. The effect of changes in commodity prices is statistically significant in both regimes for Australia, Brazil, and Russia, but only during the volatile regime for Norway's sovereign CDS spreads. The impact of changes in commodity prices is smallest for Norway's CDS spreads and greatest for Russia's. We find that the response of sovereign CDS spreads to changes in commodity prices is greater in emerging economies than in their advanced counterparts. Finally, we find evidence that increasing global financial stress raises the likelihood of a shift to a crisis state in Australia, Brazil, and Russia, but not in Norway. Additionally, commodity price fluctuations are associated with a lower probability of a transition to a crisis regime for Norway's sovereign CDS. In contrast, they appear to increase the likelihood of a switch to the volatile regime for Russia's sovereign CDS spreads.

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2 Macroeconomic and Stock Market Performance in Commodity-exporting Economies

2.1 Introduction

Small open economies that depend heavily on commodity exports are vulnerable to fluctuations in commodity prices. A substantial body of empirical research shows that changes in commodity prices are a key factor influencing macroeconomic performance in commodity-exporting countries (see, e.g., Fornero et al., 2016; Fernández et al., 2017). High commodity prices boost export earnings, which then stimulate domestic consumption and investment, thereby fostering economic growth. As recent decades have seen notable swings in commodity prices, understanding the macroeconomic impacts of shocks to commodity markets has become increasingly vital.

Although the economic effects of commodity price fluctuations have been extensively studied, previous research has largely overlooked their underlying drivers. A key insight from recent literature is that identifying the fundamental sources of commodity market shocks, which have distinct macroeconomic and asset price effects, is essential for informing appropriate policy responses (Kilian, 2009; IMF, 2012) or for necessary portfolio adjustments (e.g., Kilian and Park, 2009; Güntner, 2014). Ignoring these shocks means focusing only on average commodity price changes, which can yield misleading or inconclusive results (see Kilian, 2009).

Several studies highlight the important role of commodity prices in transmitting global shocks (see, e.g., Fernández et al., 2017; Miranda-Agrippino and Rey, 2022; Juvenal and Petrella, 2024). Commodity prices respond to shifts in macroeconomic fundamentals that affect aggregate supply and demand. Shifts in global economic and financial conditions, as well as idiosyncratic commodity market events, have been identified as key sources of commodity price fluctuations (Frankel, 2014; Juvenal and Petrella, 2024). This paper examines the significance of global shocks for macroeconomic and stock market performance in economies heavily reliant on commodity exports.

We focus on commodity-dependent countries because of their vital role in the global economy through the export of primary commodities. They account for over half of the world's economies (UNCTAD, 2019) and contribute nearly one-fifth of global GDP (Bergholt et al., 2019). Although most commodity-dependent economies are low-income and least-developed countries, some emerging economies (EMEs) and advanced economies (AEs) also fall into this category. The common view is that aggregate fluctuations in emerging economies differ from those in developed economies, showing greater volatility (Hevia, 2014). Our study examines eight commodity-exporting countries, including four advanced economies (Australia, Canada, New Zealand, and Norway) that are rarely analysed in the literature, and four emerging-market economies (Brazil, Chile, Russia, and South Africa).

Our analysis addresses the following questions: How do global shocks that drive commodity market movements affect output and stock market performance in economies dependent on commodity exports? Which shock has the most significant impact? Are the effects of these shocks similar or different across the sampled emerging and developed economies? To address these questions, we estimate country-specific structural vector autoregressive (SVAR) models using a monthly dataset spanning January 1995 to December 2019.

The SVAR methodology provides a robust, data-driven framework for analysing the dynamic interactions among economic variables. It is widely recognised that the real price of commodities is endogenous to global macroeconomic conditions (e.g., Kilian, 2009; Jacks and Stuermer, 2020). Global commodity prices respond to some of the same broader economic forces that influence domestic macroeconomic aggregates, which makes it necessary to consider reverse causality (Kilian and Park, 2009). The SVAR approach addresses reverse causality and endogeneity by allowing the modelling of both contemporaneous and lagged interdependencies among variables. Our SVAR framework links the global and domestic economies, allowing us to jointly analyse the determinants of commodity prices and domestic macroeconomic variables. Importantly, unlike the standard reduced-form vector autoregression (VAR) model, which is regarded as non-theoretical, the SVAR approach offers a coherent structural interpretation of the system's shocks by applying identification restrictions grounded in economic theory.

Our empirical strategy builds on Bjørnland (2009). Recent research shows that changes in global commodity demand, driven by unexpected shifts in real economic activity, are the primary factors behind commodity price movements, whereas supply shocks have a

lesser effect (e.g., IMF, 2012; Kilian and Zhou, 2022; Jacks and Stuermer, 2020). Therefore, we augment Bjørnland's (2009) SVAR model with a measure of global economic activity to capture unexpected changes in global real activity that influence demand across all commodities. We employ the index of world industrial production as a proxy for global economic activity (Baumeister and Hamilton, 2019).

The U.S. monetary policy interest rates (Frankel, 2008; Frankel, 2014), shifts in global risk appetite (Juvenal and Petrella, 2024), and the financialization of commodity markets (Juvenal and Petrella, 2015) have also been shown to explain fluctuations in commodity prices. We use the U.S. BAA corporate spread to capture global financial conditions (Akıncı, 2013; Epstein et al., 2019; Juvenal and Petrella, 2024) instead of the trade-weighted foreign interest rate, as in Bjørnland (2009). Unexpected changes in the BAA spread are linked to U.S. monetary policy shocks and changes in global risk appetite and uncertainty (Juvenal and Petrella, 2024). Since the sampled economies export diverse baskets of primary commodities, we utilise country-specific commodity export price indices (CXPI) from Gruss and Kebhaj (2019) to better reflect movements in global commodity prices relevant to each sampled country.

To model the domestic macroeconomic environment of a small open economy, we include measures of real output, headline inflation, the short-term nominal interest rate, the real exchange rate, and the real aggregate stock market index. Most countries lack a reliable monthly indicator of aggregate output. The monthly industrial production index, a commonly used alternative, is often considered inadequate because it captures only a limited segment of output. We address this limitation by constructing a monthly real GDP series from quarterly real GDP data using the Chow-Lin interpolation methodology (Chow and Lin, 1971), aided by monthly indicator variables.

We employ short-run identifying restrictions to identify shocks, relying on the small-open-economy assumption that the global economy contemporaneously impacts the domestic macroeconomy, while excluding contemporaneous feedback from domestic variables to the global economy. Consistent with the existing literature, we identify global activity (GA) shocks as innovations in global economic activity (IMF, 2012; Bjørnland and Thorsrud, 2016), and global financial risk (GFR) shocks as innovations in a measure of global financial conditions (Akıncı, 2013). We also identify commodity (specific) price (CSP) shocks as innovations in the CXPI, which are contemporaneously unrelated to global economic activity and global financial risks (Bjørnland and Thorsrud, 2016; Jacks and Stuermer, 2020).

We compute structural impulse responses and forecast-error variance decompositions from the estimated country-specific SVAR model to evaluate the effects of shocks. An impulse response function shows the impact of a structural shock on the modelled variables, illustrating how the response evolves over the forecast horizon. Forecast-error variance decompositions measure the relative importance of a shock in explaining variations in each variable.

This chapter contributes to various areas of the literature. Its main contribution is to quantify the relative importance of shocks to commodity export prices, global economic activity, and global financial conditions on real output and equity market performance in countries dependent on commodity exports. Investigating shocks from unexpected changes in global economic activity and financial conditions is especially relevant given their influence on commodity markets.

Recent research on the effects of commodity price shocks has largely focused on identifying shocks to global oil prices and their influence on macroeconomic variables (e.g., Kilian, 2009) and stock markets (e.g., Kilian and Park, 2009; Basher et al., 2012) in oil-exporting and advanced oil-importing economies. There has been less emphasis on analysing shocks within broader commodity markets and their impact on the economies of other primary commodity exporters. Our study differs from most existing research by investigating countries classified as exporters of agricultural, energy, or metal commodities. Instead of relying solely on oil prices or a single commodity export price, we utilise country-specific commodity price indices with time-varying weights to reflect changes in the mix of commodities traded over time (Gruss and Khebaj, 2019).

This article also connects to the growing empirical research on how global financial risk shocks influence overall economic activity (Akıncı, 2013; Epstein et al., 2019; Horvath and Zhong, 2019) and asset prices (Rey, 2015; Yildirim, 2016; Horvath and Yang, 2024). However, most of these studies mainly focus on emerging markets and often overlook shocks to global economic activity or commodity markets. Finally, our analysis focuses on a group of emerging and developed economies characterised as small open economies. This enables us to compare how macroeconomic aggregates may respond differently to global shocks across EMEs and AEs, rather than focusing on a single country group.

We find that GA shocks, which temporarily ease global financial conditions and raise all the CXPIs, have statistically significant expansionary effects on output across the sampled countries, with the notable exception of New Zealand. However, the expansionary

impact on real GDP appears more pronounced in emerging economies than in advanced economies, with Russia exhibiting the largest peak effect of approximately 0.3%, followed by Brazil at approximately 0.2%. We find considerable cross-country heterogeneity in the responses of equity markets to GA shocks. The positive response of stock markets in Australia, Canada, Norway, and South Africa to the shocks is statistically significant in the short term, somewhat significant in Brazil, and insignificant in Chile and Russia.

In contrast, an increase in the BAA spread (indicating a deterioration in global financial conditions) that triggers a marked contraction in global economic activity and an immediate, significant decline in all CXPIs leads to an immediate, statistically significant decline in equity markets across all countries. Our results indicate that among the sampled countries, the stock markets of Russia and Brazil are the most affected, with the largest declines of approximately 5.5% and 5%, respectively. However, GFR shocks generally have statistically insignificant contractionary effects on real GDP across most countries, except Brazil. This contrasts with most previous studies, which document that GFR shocks significantly reduce economic activity in AEs (e.g., Epstein et al., 2019) and EMEs (e.g., Akinci, 2013; Horvath and Yang, 2024).

On average, a one-standard-deviation increase in commodity export prices appears to have minimal effects on global economic activity and insignificant effects on global financial conditions. We find that CSP shocks have negligible to small effects on real output across most of the sampled countries. The shock has minimal effects on equity markets in most countries, triggering an instantaneous positive response that is only briefly statistically significant. The notable exception is Chile, where the positive response to CSP shocks remains statistically significant for over three years.

Real GDP variance decompositions correspond with the estimated impulse response functions, indicating that GA shocks are the most influential external shocks in explaining output fluctuations, with greater explanatory power in emerging economies. Conversely, global financial risk and commodity-specific price shocks are generally less relevant for output fluctuations. We find that, on average, global shocks have a larger combined contribution to EMEs' output fluctuations than in AEs. Notably, in Brazil and Russia, the combined contribution of external shocks to output fluctuations peaks at the 12-month forecast horizon at approximately 52% and 61%, respectively.

Stock market variance decompositions indicate that GFR shocks have a markedly stronger influence on stock markets across all sampled countries, particularly in the short

term. They account for significant portions of stock market fluctuations in Australia, Brazil, Canada, Chile, New Zealand, and Norway, with peak contributions ranging from 23% to 33%. The shocks explain a relatively modest share of stock market variability in Russia (15%) and South Africa (19%). GA shocks contribute modestly in Australia, Canada, Norway, and South Africa, representing 16%–19% at the six-month forecast horizon, while their impact is smaller in Chile, New Zealand, and Russia. The effect of CSP shocks is much smaller in most countries, except Chile. On average, the combined influence of global shocks on AE stock markets exceeds that on EMEs, especially at short- to medium-term forecast horizons.

We also perform a series of sensitivity analyses to evaluate the robustness of our baseline results. These checks include using the VIX as an alternative measure of global financial risk, employing the domestic industrial production index as an indicator of total economic output, estimating with quarterly data, and conducting subsample analyses. The results generally support the findings from the benchmark analyses.

Understanding how shocks in global commodity markets influence macroeconomic dynamics is essential for guiding macroeconomic policy. Fluctuations in stock market values impact household wealth and overall consumption, thereby influencing aggregate demand and economic growth (Caballero and Simsek, 2024). Stock prices reflect credit risk, which correlates positively with firms' financing costs (Mishkin, 2001). According to Tobin's Q Theory (Tobin, 1969), economic agents incorporate stock market valuations into their investment decisions. This research article may also be valuable for investors developing portfolio, investment, and hedging strategies. Investors form and revise their expectations about future macroeconomic policy, which, in turn, influences their attitudes towards risk.

The rest of the paper is organised as follows: Section 2 covers the theoretical underpinnings, a literature review, and the development of hypotheses. Section 3 describes variable selection and gives an overview of the data. Section 4 addresses methodological issues, including the econometric model and the restrictions imposed to identify structural shocks. In Section 5, we present and analyse the empirical results, focusing on the impulse response functions (IRFs) and the forecast error variance decomposition (FEVD). Section 6 summarises robustness checks. Finally, the last section concludes the paper.

2.2 Relationship with the Literature and Hypothesis Development

This section provides a brief overview of the relevant theoretical and empirical literature that supports the analysis. Additionally, it outlines the hypotheses examined in this study.

2.2.1 Theoretical underpinnings

An increase in global real economic activity generally boosts demand for commodity exports, leading to higher real commodity prices (Kilian, 2009; Frankel, 2014; Juvenal and Petrella, 2015). When global financial conditions ease—due to looser monetary policy or strong global risk appetite—they can enhance the outlook for the world economy, thereby raising commodity prices. Lower interest rates decrease the cost of holding inventories, boosting inventory demand and raising commodity prices as demand for commodities grows (Frankel, 2008; Frankel, 2014). However, rising commodity prices may induce domestic inflation in major economies, prompting central banks to tighten monetary policy. Such measures can worsen global financial conditions, increase risk aversion, and potentially slow economic activity (Juvenal and Petrella, 2024).

Improved global financial conditions, which can lead to high commodity prices, can trigger an appreciation of the currencies of commodity-exporting countries against the US dollar. A weak US dollar can boost the global economy by easing financial conditions and facilitating international trade (Rey 2015). A weak dollar improves balance sheets because the local-currency value of dollar-denominated liabilities declines, thereby enhancing creditworthiness and lowering sovereign spreads. A low-interest-rate environment with an appreciating domestic currency (a weak dollar) encourages capital inflows as investors seek arbitrage profits and capital gains. Overall, this should lead to increased investment, output growth, and rising asset prices (Horvath and Yang, 2024).

High commodity prices enhance an exporting country's terms of trade, thereby increasing real income, reducing economic uncertainty, lowering sovereign risk, and strengthening financial stability (see Drechsel and Tenreyro, 2018). The expectation is that both consumption and investment rise, decreasing unemployment and thus boosting economic activity. A decline in sovereign risk, combined with improving macroeconomic fundamentals, can attract capital inflows, which stimulate domestic economic activity and asset prices (Juvenal and Petrella, 2024). However, a period of high growth may also lead to

demand-side inflation, necessitating a contractionary monetary policy response (e.g., raising short-term interest rates).

Commodity-exporting countries benefit from rising commodity prices through positive income and wealth effects (Bjørnland, 2009). Higher commodity prices cause a transfer of wealth from commodity importers to exporters. The income effect occurs because increased global commodity prices raise the real wage. An income windfall spent on domestically produced goods and services enhances national wealth and domestic demand, thereby boosting economic activity. Elevated revenues in the commodity-producing sector can lead to substantial investment and business opportunities across the economy, increasing demand for labour and capital.

A positive commodity price shock can lead to an increase in real GDP in economies where the commodity sector has strong links to other sectors. According to economic theory, a rise in global commodity prices boosts export revenue and causes the real exchange rate to appreciate. This generally benefits the more profitable sectors but can harm the overall economy by increasing wage costs and reducing international competitiveness. This effect, known as Dutch disease, is mainly seen in resource-rich economies (see Corden and Neary, 1982; Charnavoki and Dolado, 2014; Bjørnland and Thorsrud, 2016).

Financial markets aggregate information about the economy and corporate performance into asset prices. Theoretical models suggest that stock prices reflect the present value of future net earnings (Huang et al., 1996). Consequently, stock prices change in response to factors influencing expected cash flows and the discount rate. Commodity prices can impact stock prices directly, by affecting current and future cash flows, or indirectly, by influencing the interest rates used to discount those cash flows (Basher et al., 2018). Additionally, nominal interest rates are influenced by expected inflation and anticipated interest rate movements.

As noted in the preceding section, rising stock prices and dividends can stimulate consumption and investment through the wealth and income channels, thereby boosting economic activity and real GDP.

2.2.2 Commodity prices and global macroeconomic factors

This paper draws on the literature regarding factors influencing changes in global commodity prices. Recent market booms and busts are mainly associated with macroeconomic fundamentals (Borensztein and Reinhart, 1994; Carter et al., 2011).

UNCTAD (2023) notes that the combined effects of supply and demand shocks have contributed to the high volatility of commodity prices. Several studies find that commodity price fluctuations are primarily driven by changes in global demand, linked to unexpected shifts in global real economic activity, while supply shocks tend to have a lesser impact (see, e.g., Kilian, 2009; Frankel, 2014; Juvenal and Petrella, 2015; Jacks and Stuermer, 2020). The widespread increase in commodity prices during the 2000s is largely attributed to strong global demand, fuelled by the strong economic growth in emerging markets such as China and India. A slowdown in global economic activity is generally regarded as the main factor behind the 2015 decline in oil prices (Baumeister and Kilian, 2016).

In addition to demand and supply fundamentals, global financial factors are also recognised as significantly affecting fluctuations in commodity prices. One argument is that the increased involvement of financial investors in commodity markets (financialization) contributed to the sharp rise in commodity real prices during the 2000s (see Frankel, 2014; Juvenal and Petrella, 2015). A growing body of literature suggests that monetary policy can influence commodity prices. Frankel (2008) argues that rising interest rates can decrease the spot prices of commodities through three channels: (i) by increasing inventory holding costs, which reduces the demand for storable commodities; (ii) by encouraging speculators to shift from commodity contracts to the bond market; and (iii) by raising incentives to extract exhaustible commodities to reinvest the proceeds for higher returns in the present. Frankel (2008) and Akram (2009) empirically demonstrate that monetary policy negatively impacts global commodity prices.

Using a financial stress indicator, Chen et al. (2014) examine the role of unexpected changes in global financial market conditions and find that a positive financial shock is associated with a statistically significant decline in oil prices. Juvenal and Petrella (2024) show that commodity price fluctuations are linked to shifts in U.S. monetary policy and changes in global risk appetite, both of which are key determinants of the global financial cycle (Rey, 2015). Their findings indicate that reductions in the BAA spread (eased global financial conditions) lead to a surge in export prices.

Global commodity prices are quoted in US dollars, and most commodity contracts are settled in dollars. A depreciation of the dollar effectively boosts the purchasing power of foreign consumers, thereby increasing global demand for commodities and their prices. Akram (2009) provides empirical evidence supporting a negative correlation between commodity prices and the U.S. dollar.

2.2.3 Global shocks and real activity

Our paper relates to the empirical literature on the economic implications of commodity price shocks. Kilian (2009) emphasises that the macroeconomic impacts of oil price fluctuations depend on the underlying cause of the shock. Following Kilian (2009), a substantial body of literature on oil price shocks has developed, but it mainly focuses on advanced oil-importing economies.

Fewer studies have examined the macroeconomic impacts of general commodity price shocks in commodity-exporting countries. Charnavoki and Dolado (2014) demonstrate that increases in commodity prices, driven by global demand, raise Canada's output, whereas increases caused by negative commodity supply shocks result in Dutch disease effects. Bjørnland and Thorsrud (2016) find that increases in commodity prices driven by rising global demand benefit the economies of Australia and Norway. In contrast, they observe that price changes not linked to global activity tend to have less positive effects, leading to Dutch disease effects in Australia.

Using an SVAR model, da Silva Souza and Fry-McKibbin (2021) demonstrate that commodity demand shocks, rather than commodity price shocks, significantly influence Brazil's output, with no evidence of Dutch disease in the long run. They also show that positive innovations in global liquidity increase real commodity prices and boost Brazil's domestic output. An IMF (2012) study finds that global demand-driven commodity market shocks positively and significantly impact exporters' activity and external balances. In contrast, a shock to a commodity's global production has a limited economic effect. Pedersen (2019) examines the effect of copper prices on Chile's economy and finds a significant positive impact of demand shocks on GDP, but no significant response to supply-side or specific copper-demand shocks.

A substantial body of literature investigates the effects of commodity shocks on aggregate fluctuations in small open economies. Mendoza (1995) and Kose (2002) argue that terms-of-trade shocks are important drivers of aggregate fluctuations in small EMEs. Conversely, Schmitt-Grohé and Uribe (2018) find that the contribution of terms-of-trade shocks to aggregate fluctuations is only 10 per cent in SVAR models. Fernández et al. (2017) estimate that three commodity prices and a global interest rate explain about one-third of output fluctuations.

Our analysis also relates to a growing body of literature on the international transmission of financial shocks. It is suggested that commodity prices act as conduits for

global shocks. Several studies examine the relevance of global financial factors to overall fluctuations in small open economies. As noted by Horvath and Yang (2024), the literature lacks consensus on the impact of global financial risk on aggregate fluctuations. Akıncı (2013) and Yildirim (2022) show that shocks from global financial risk account for a significant portion of macroeconomic volatility in emerging markets. In contrast, Epstein et al. (2019) find only a minor role for these shocks. Choi (2018) demonstrates that the VIX has a substantial effect on EME output but is insignificant for U.S. output. Miranda-Agrippino and Rey (2022) report that a tightening of global financial conditions does not significantly influence global growth.

Epstein et al. (2019) demonstrate that shocks to global financial risk significantly reduce GDP, investment, and employment in AEs more than in EMEs. Horvath and Zhong (2019) investigate how external demand, foreign interest rates, and uncertainty shocks affect EMEs, finding that declines in external demand and rises in external interest rates and uncertainty (measured by the VIX index) lead to higher unemployment, lower stock market returns, and a depreciation of the domestic currency. Yildirim (2022) examines the impacts of global financial risk shocks on EMEs, noting that these shocks cause both contractionary and inflationary effects. Horvath and Yang (2024) show that increased global financial risk notably raises EME borrowing costs and reduces equity returns, thereby harming domestic economic activity.

Using the panel local projections method, Juvenal and Petrella (2024) analyse the relationship between commodity price fluctuations, the global financial cycle, capital flows, and economic outcomes in emerging and developing economies. They find that easier global credit conditions (due to either looser U.S. monetary policy or a lower global risk appetite) increase export prices and output, reduce EMBI spreads, and encourage greater capital flows. They also observe that surges in export prices, driven by commodity price fluctuations, boost domestic GDP.

2.2.4 Global shocks and stock market performance

Existing research highlights the considerable impact of commodity prices on the financial sector. For instance, Kinda et al. (2018) indicate that negative shocks to commodity prices are associated with currency depreciation and drops in equity and bond values, which in turn weaken a country's financial system.

The empirical research on commodity prices and stock markets primarily focuses on oil shocks, with most studies concentrating on the U.S. and other advanced economies. As expected, research by Bjørnland (2009), Park and Ratti (2008), and Filis and Chatziantoniou (2014) shows that stock markets in oil-exporting countries tend to react positively to rising oil prices.

Building on Kilian (2009), Kilian and Park (2009) show that global oil supply shocks are less significant to the U.S. stock market than aggregate demand or oil-specific demand shocks. Wang et al. (2013) demonstrate that the stock markets of oil-exporting countries do not react to supply-side oil price shocks but respond positively to positive aggregate demand shocks. They find that positive precautionary demand shocks have significant positive responses in Canada, Saudi Arabia, Norway, and Russia. Güntner (2014) examines stock returns in six OECD countries and finds that, while oil supply shocks have limited effects, aggregate demand shocks boost real stock returns.

Fewer studies explore the relationship between general commodity prices and stock markets. Johnson and Soenen (2009) investigate the importance of commodity prices as a factor affecting short-term stock market behaviour in South American countries, showing that stock markets have a contemporaneous relationship with commodity prices. Basher et al. (2019) examine the effects of commodity price shocks on realised stock market volatility in Canada, Australia, Russia, and Brazil, concluding that positive commodity price shocks are associated with lower realised stock market volatility.

Rey (2015) demonstrates that the global financial cycle negatively impacts stock prices. Bekaert and Hoerova (2017) note that risk aversion and economic uncertainty are important drivers of asset price movements. Miranda-Agrippino and Rey (2022) find that a tightening of US monetary policy worsens global financial conditions, causing the VIX to spike and reducing global asset prices (including commodity prices). Yildirim (2016) finds that global financial conditions significantly negatively influence domestic equity prices in EMEs. Hallam (2022) reports that EMEs' macroeconomic activity and asset prices decline markedly in response to tighter global financial conditions. Horvath and Rothman (2021) find that EME output, investment, consumption, and house and stock prices respond substantially negatively to an increase in the US mortgage spread.

2.2.5 Hypothesis development

An increase in global economic activity is likely to boost demand for commodity exports, driving commodity prices higher. Higher export prices improve the terms of trade for exporting countries, increasing export revenues and fiscal income. This, in turn, stimulates consumption and investment, thereby supporting real economic activity. Stock prices tend to rise as firms' expected cash flows increase and economic uncertainty decreases, consistent with the net present value principle. Merton (1973) suggests that variables affecting future consumption and investment prospects should be priced as risk factors in equilibrium. We propose the following hypothesis:

Hypothesis 1: Increasing global economic activity positively influences real activity and aggregate stock market performance.

Rising global financial risks are linked to strict monetary policies and increased investor risk aversion (Juvenal and Petrella, 2024). Tighter global financial conditions limit global economic growth, decrease demand for commodities, and consequently lower international commodity prices. A drop in export earnings reduces domestic consumption—as national income falls—and investment, since weakened balance sheets raise lending risks and increase the cost of capital, further dampening economic activity. Falling asset prices across the globe can be attributed to the discount rate effect, in which rising interest rates and risk premiums lower asset values, and the cash flow effect, in which a worsening economic outlook diminishes expected returns (Rey 2015). Additionally, as risk appetite wanes, investors tend to shift portfolios towards safer assets, decreasing capital inflows and putting downward pressure on asset prices (Yildirim, 2022). Therefore, we also examine the following hypotheses.

Hypothesis 2: Increased global financial risks negatively correlate with stock market performance and real activity.

Hypothesis 3: High commodity prices have a positive impact on real activity and stock market performance.

2.3 Data overview

2.3.1 Country characteristics

Our country sample includes four emerging economies (Brazil, Chile, Russia, and South Africa) and four advanced economies (Australia, Canada, New Zealand, and Norway). According to UNCTAD (2019) criteria, all the countries except Canada and South Africa are classified as highly dependent on commodity exports.[1] Table 2.1 shows the average proportion of commodity exports in total merchandise exports and GDP. Australia, Chile, and South Africa mainly rely on mineral commodities. Canada, Norway, and Russia primarily export energy, while Brazil and New Zealand predominantly export agricultural products (UNCTAD 2019).

The sampled countries have relatively open, trade-exposed economies with floating exchange rate regimes. These economies also feature well-developed and liquid stock markets, with macroeconomic and financial data available over a significant period.

2.3.2 Sample period and frequency

The Structural Vector Autoregression (SVAR) analyses use monthly time-series data from January 1995 to December 2019, excluding Brazil, whose sample starts in January 1996. This timeframe encompasses periods of notable fluctuations in global commodity markets, the 2007-2009 Great Recession, and several geopolitical and financial crises, including the 1997 Asian financial crisis and the Russian financial crisis of 1998-1999.

Monthly data are preferred over quarterly data because the stock market is a rapidly changing variable that adjusts quickly to current economic conditions over shorter timescales. Monthly data capture fluctuations that quarterly data might mask. Additionally, using monthly data enhances the validity of the identification assumptions underlying our structural VAR model. However, as a robustness check, we also re-estimate our country-specific SVAR models with quarterly data, obtained by averaging the higher-frequency data.

2.3.3 Variables

The SVAR model variables selected must be consistent with a New Keynesian (inflation-targeting) small open economy theoretical framework to capture interactions between the

[1] A commodity-dependent economy has more than 60% of its total merchandise exports made up of commodities (UNCTAD 2019).

identified shocks and the central bank's monetary policy responses, as an inflation-targeting central bank aims to counteract any inflationary stimulus from the shocks (Bjørnland, 2009).[2] To assess the impact of global shocks, the SVAR model interacts a set of global variables that represent worldwide economic conditions with a set of domestic variables reflecting the domestic economy. Table 2.2 provides an overview of the dataset and lists the sources.[3]

2.3.3.1 Global variables

We utilise the monthly *index of world industrial production* (WIP) for the OECD and six major emerging markets as a proxy for global real economic activity (Baumeister and Hamilton, 2019). A positive shock to global economic activity (GEA) is expected to boost demand for industrial commodities, thereby increasing global commodity prices.

Moody's U.S. corporate *BAA-Treasury spread* (BAA spread), which measures the yield difference between Baa-rated corporate bonds and 10-year Treasury bonds, serves as a proxy for global financial risk (Akıncı, 2013; Juvenal and Petrella, 2024). The spread is widely used to evaluate financial crises and shows strong correlations with banking panics, major financial downturns, and significant political shocks. It is also regarded as an indicator of liquidity shortages during credit crunches (see Bordo and Duca 2022). The world industrial production index and the BAA spread are common across the sampled countries.

Our measure of commodity prices is the *country-specific commodity export price indices (CXPI),* which are constructed by Gruss and Kebhaj (2019) and sourced from the International Monetary Fund (IMF) Commodity Terms of Trade database.[4] The monthly CXPIs are calculated for each country as trade-weighted changes in the global real prices of 45 individual commodities, including agricultural raw materials, energy, food and beverages, and metals. Gruss and Kebhaj (2019) estimate

$$\Delta Log(Index)_{i,t} = \sum_{k=1}^{K} \Delta P_{k,t} \Omega_{i,k,t} \tag{2.1}$$

where $P_{k,t}$ is the logarithm of the real price of commodity k in month t in US dollars; $\boldsymbol{\Omega_{i,k,t}}$ is the period t country- and commodity-specific time-varying weight. The time-varying

[2] In the appendix, we briefly present a New-Keynesian small open economy model, as summarised by Dungey and Pagan (2009).
[3] Seasonal adjustment is performed using the X-13 ARIMA-SEATS procedure in EViews 12 when necessary.
[4] https://data.imf.org/?sk=2CDDCCB8-0B59-43E9-B6A0-59210D5605D2

weights (based on trade flows over the preceding 3 years to reflect changes in the commodity export basket) are given by:

$$\Omega_{i,k,t} = \frac{1}{3}\sum_{s=1}^{3} \omega_{i,k,\tau-s} \tag{2.2}$$

where $\omega_{i,k,t} = x_{i,k,\tau}/\sum_{k=1}^{K} x_{i,k,\tau}$ is the weight of individual commodities, $\boldsymbol{x_{i,k,t}}$ is the export value (in US dollars) of commodity *k* by country ***i*** in year $\boldsymbol{\tau}$ **(**the calendar year corresponding to period ***t***). This approach guarantees that the changes in price indexes reflect variations in the relevant commodity prices for each country at every point in time.

2.3.3.2 Domestic variables

We include measures of output and headline inflation, which are the domestic target variables in an inflation-targeting framework. We use real GDP as an indicator of economic activity. GDP provides a broader measure of economic activity than the industrial production index (IPI); however, it is reported quarterly. The Chow–Lin interpolation procedure is used to construct a monthly GDP series, ensuring that the sum of the interpolated points matches the source data. We use industrial production and retail sales as high-frequency indicator series, except in Brazil, where we rely solely on industrial production, and in New Zealand, where we use the employment rate and merchandise exports instead. *CPI inflation* is measured by the annual growth rate of the monthly consumer price index (CPI). We use inflation rather than the price level as the monetary policy objective, since most countries target inflation. However, our aim is not to identify monetary shocks.

The *short-term interest rate* (SR), based on three-month money market rates, is used as a proxy for the monetary policy instrument. Additionally, we include the bilateral U.S. dollar *real exchange rate* (rex), calculated by log-transforming the nominal exchange rate and adjusting for domestic and foreign price levels, as follows:

$$rex_t = ex_t + CPI_t^{US} - CPI_t^{d} \tag{2.3}$$

where at time *t*, ex_t is the nominal exchange rate quoted in direct form (i.e., $ex = domestic\ currency/US\ dollar$), and CPI_t^{US} and CPI_t^{d}, respectively, are the foreign and domestic price levels measured by the consumer price indices in log terms. An increase in the ratio implies a depreciation of the domestic currency.

The *real equity index* (SPX) serves as a proxy for asset prices, reflecting firms' expected profitability and investment levels, which are linked to a nation's future economic

activity and growth. We calculate the monthly nominal stock market index as the simple arithmetic average of daily aggregate MSCI stock price index data. The real equity index, expressed in logarithmic terms, is obtained by deflating the nominal equity index using the consumer price index.

2.4 Empirical Framework

2.4.1 Specifying the Structural Vector Autoregressions

A key methodological concern in the analysis is how to specify the SVAR model when some variables are integrated, possibly cointegrated, or exhibit patterns indicative of deterministic trends.

Stationary or Integrated Variables. Pre-tests for unit roots and potential cointegration reveal a mix of stationary and non-stationary variables across the sampled countries. There is also evidence that some integrated variables are cointegrated, suggesting long-term equilibrium relationships. Using differenced VAR models is not advisable, as they discard long-run information. Converting the VAR into a vector error-correction model (VECM) helps reduce uncertainty and bias in impulse response estimates, especially in small samples. However, this approach involves risks because pre-tests for unit roots and cointegration used to specify and identify VAR models have limitations.

Unit root tests are known for their low power to distinguish between a null hypothesis of a unit root and a stationary alternative, so some uncertainty remains about whether a variable is truly integrated (Kilian and Lütkepohl, 2017). Failing to reject the null does not confirm it; instead, it indicates a lack of strong evidence to dismiss the presence of a unit root altogether, as the null may hold or the test might lack sufficient power against the alternative. Furthermore, research has demonstrated that unit root pretests are invalid when the dominant root is close to unity, known as local-to-unity (Gospodinov et al., 2013; Kilian and Lütkepohl, 2017).

Another issue is the uncertainty regarding whether the integrated variables are cointegrated. Statistical tests for cointegration often have limited power, which can introduce estimation uncertainty. The tests assume precise knowledge of the number of unit roots and cointegration relationships, which, if incorrect (such as when the system contains near-unit-root processes), can lead to inconsistent VAR estimates and weaken inference (Elliott, 1998; Kilian and Lütkepohl, 2017).

Incorrectly imposing a unit root or the cointegrating rank during estimation can produce impulse response estimates that are highly distorted and misleading, thereby weakening inference (Gospodinov et al., 2013; Kilian and Lütkepohl, 2017). To avoid these issues, some researchers recommend specifying the VAR model in levels. While not imposing unit root and cointegration restrictions when they exist may reduce efficiency, the estimates will still be consistent (Sims et al., 1990; Hamilton, 1994; Kilian and Lütkepohl, 2017). An unrestricted VAR in levels, with an intercept, encompasses both integrated and potentially cointegrated VAR models (see Hamilton, 1994; Kilian and Lütkepohl, 2017). Kilian and Lütkepohl (2017) argue that, if the VAR is properly specified in levels, impulse response analyses remain asymptotically valid even without imposing these restrictions (Sims et al., 1990). Gospodinov et al. (2013) demonstrate that a VAR in levels generally provides more robust estimates when there is uncertainty about the size of the roots and the co-movement between variables than models that depend on pre-tests for unit roots and cointegration.

Gospodinov et al. (2013) suggest that the most dependable approach for practical applications is to estimate the VAR in levels and identify structural impulse responses using short-run restrictions. Therefore, in our cross-country analysis, we use an SVAR model in levels to minimise issues related to model misspecification and the risk of inaccurate inference. We apply short-run restrictions for identification to capture the dynamic effects of shocks.

Deterministic trends. Tests using a regression model with a constant and a deterministic trend show that most variables, both global and country-specific, display a statistically significant deterministic time trend.

Existing research employs various methods to address deterministic trends in VAR models. Bernanke (1986) demonstrates that adding a deterministic time trend enhances the explanatory power of money in output autoregressions. Bjørnland (2009) justifies including a linear trend by noting that, in conducting monetary policy, central banks adjust the policy interest rate in response to deviations from the natural rate of output (potential output) rather than the level of output itself. In the literature, deterministically detrended output is often used as a proxy for the output gap, which measures the difference between actual and potential output. Moreover, Bjørnland (2009) emphasises that including a trend can also help ensure the invertibility of the VAR when variables are nonstationary.

We therefore follow studies such as Dungey and Pagan (2000), Dungey et al. (2014), and Da Silva Souza and Fry-McKibbin (2021) by demeaning and detrending the variables before estimating the VAR models, using a regression of the form:

$$y_t = \alpha + \beta t + \varepsilon_t, \tag{2.4}$$

where ε_t is a white noise disturbance term and β is the coefficient of time. This is consistent with the approach taken in many New Keynesian DSGE models (see Lubik and Schorfheide, 2005; Dungey and Pagan, 2009).

We take natural logs of all variables except the BAA spread, short-term interest rates, and CPI inflation, which are expressed as percentages. The demeaned and detrended WIP, CXPI, real GDP, the real exchange rate, and the stock market index are therefore characterised as log deviations from a linear trend, whereas the BAA spread, CPI inflation, and the short-term interest rate are characterised as deviations from their time trends.

While adding a deterministic time trend does not change the asymptotic results, it can increase small-sample bias in the VAR model's slope estimates, possibly reducing the accuracy of asymptotic approximations in small samples (Kilian and Lütkepohl, 2017). Consequently, we perform a sensitivity analysis with non-detrended variables, which indicates that our main conclusions remain largely unchanged.

2.4.1.1 The SVAR model

As in Kilian and Lütkepohl (2017), we consider a K-dimensional time series $y_t, t = 1, \ldots, T$, with a data-generating process well-approximated by a p-order vector autoregression. We consider the SVAR specification of the form:

$$A_0 y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t \qquad u_t \sim iid\ N(0, \Sigma_u) \tag{2.5}$$

where elements of the $K \times 1$ vector u_t are errors assumed to be zero-mean and independently and identically distributed (*iid*) white noise with a covariance matrix $\mathbb{E}(u_t u_t') = \Sigma_u$. The invertible $K \times K$ matrix

The K distinct elements of u_t are mutually uncorrelated so that Σ_u is a diagonal matrix which, when normalised, yields $\mathbb{E}(u_t u_t') = \Sigma_u = I_k$. The disturbances are interpreted as structural shocks because of the zero covariances of u_t (i.e., $\mathbb{E}(u_t u_{t+s}') = 0, \text{for all } s \neq 0$). We further assume that the K model variables are driven by K distinct shocks so that the covariance matrix Σ_u is full-rank.

Equation (2.5) cannot be estimated directly because contemporaneous effects among the variables would induce simultaneity bias, as the regressors and error terms are correlated. If the A_0 matrix is invertible, the structural VAR model has an associated usable reduced-form model in which all right-hand-side variables are lagged or predetermined. The reduced-form representation has the form:

$$\begin{aligned} y_t &= A_0^{-1}A_1 y_{t-1} + \cdots + A_0^{-1}A_p y_{t-p} + A_0^{-1}u_t \\ &= B_1 y_{t-1} + \cdots + B_p y_{t-p} + \varepsilon_t, \end{aligned} \tag{2.6}$$

where $B_i = A_0^{-1}A_i,\ i = 1, \ldots, p,$ are the reduced-form lag matrices capturing all the dynamics, and $\varepsilon_t = A_0^{-1}u_t$ is the reduced-form disturbance vector. Thus, unlike the structural innovations u_t which are orthogonal, the reduced form innovations ε_t are mutually correlated because they are weighted averages of the mutually uncorrelated structural errors u_t where the weights are the elements of A_0^{-1}, the structural impact multiplier matrix. They have the properties $\mathbb{E}[\varepsilon_t] = A_0^{-1}\mathbb{E}[u_t] = 0$ and $\mathbb{E}(\varepsilon_t\varepsilon_{t+s}') \equiv \Sigma_\varepsilon = A_0^{-1}A_0^{-1\prime}$.

The dynamics of the reduced form model in equation (2.6) are highlighted by expressing it in terms of the lag operator as follows:

$$\begin{aligned} y_t - B_1 y_{t-1} - \cdots - B_p y_{t-p} &= \varepsilon_t \\ \left(I_k - B_1 L - \cdots - B_p L^p\right) y_t &= \varepsilon_t \\ B(L) y_t &= \varepsilon_t, \end{aligned} \tag{2.7}$$

where $L^k y_t = y_{t-k}$ and $B(L) = I_k - B_1 L - \cdots - B_p L^p$ denotes the autoregressive lag polynomial. A *VAR(p)* model is stable (and thus covariance stationary) if

$$\det\left(B(z)\right) = \det\left(I_k - B_1 z - \cdots - B_p z^p\right) \neq 0 \quad \forall z \in \mathbb{C}, |z| \leq 1, \tag{2.8}$$

where $\mathbb{C}$ denotes the set of complex numbers (see Kilian and Lütkepohl, 2017). That is, y_t is stable if all the roots of the determinantal polynomial lie outside of the complex unit circle or, equivalently, if the (inverse) roots of the polynomial all lie inside the unit circle. The stability of the process ensures the existence of an inverse VAR operator.

2.4.1.2 Short-run Structural Restrictions

To disentangle the structural innovations, we estimate the model using the short-run A-B model restrictions of Amisano and Giannini (1997). We start from the reduced form error representation in equation (2.7), which can be written as

$$A_0 B(L) y_t = A_0 \varepsilon_t = C u_t, \tag{2.9}$$

with $\Sigma_u = I_K$ such that $\Sigma_\varepsilon = A_0^{-1} C C' A_0^{-1\prime}$. The restrictions on A_0 take the form of assumptions about the structure of contemporaneous feedback of variables in the SVAR and the C matrix restrictions control the variance-covariance matrix of the structural innovations.

The diagonal elements of *C* are restricted to unity, while the diagonal elements of the recursive impact matrix A_0 are left unrestricted. This means there is a total of K^2unknown values in the structural model. Since Σ_ε is symmetric, it has only $(K^2 + K)/2$ distinct elements. A further $(K^2 - K)/2$ restrictions on the system are therefore required for exact identification of the structural model. We impose a recursive structure on the short-run parameters so that the $K \times K$ matrix A_0 has a lower-triangular form. Since A_0 (and hence A_0^{-1}) is lower triangular, it has $(K^2 - K)/2$ zero parameters, ensuring that the shocks and their associated impulse responses are just-identified.

A unit innovation in the structural shocks defined here is typically an innovation of one standard deviation. Therefore, the estimated structural impulse responses are the variables' responses to one-standard-deviation shocks (Kilian and Lütkepohl, 2017).

2.4.1.3 Identifying Restrictions

Assuming a small-open-economy framework, domestic variables do not contemporaneously influence foreign variables. Therefore, structural shocks are identified by applying lower-triangular restrictions to the contemporaneous parameter matrix A_0. The world industrial production index is regarded as the most exogenous variable, with the assumption that the BAA spread and the CPXI do not impact global economic activity within the same month. Among the external variables, the CXPI is placed last to reflect the role of commodities as financial assets, which respond immediately to news about global economic activity and financial conditions (see Fornero et al., 2016).

Empirical research on small open economies often treats global commodity prices as exogenous because individual commodity-exporting countries are seen as lacking the market power to influence global price movements. However, some countries' commodity exports may account for a dominant or significant market share, granting them some market influence. Additionally, fluctuations in the CXPIs may reflect changes in the composition of commodity exports, which are partly endogenous (for example, due to supply responses to price shifts) or influenced by domestic export and development policies (Carpantier, 2021). In line with the existing literature (e.g., Bjørnland, 2009; Dungey et al., 2014), we relax the strict price-taker assumption, allowing these countries to have some degree of market influence. As a result, shocks originating within the domestic sector do not

contemporaneously impact global sector variables; however, they can affect global markets over time through lagged effects.

The standard SVAR literature on monetary policy indicates that, as a real variable, output responds with a lag to shocks to CPI inflation and to monetary and financial variables (Abouwafia and Chambers, 2015; Sims, 2007). The reasoning is that firms do not immediately adjust output and prices in response to unexpected changes in financial signals or monetary policy; however, they can respond quickly to shocks to commodity prices (Raghavan et al., 2012).

Most commodity exporters have implemented explicit inflation-targeting policies to counter potential inflationary pressures that might emerge after a shock to commodity export prices (Hevia et al., 2013). A common assumption in the literature, which we adopt, is that the domestic short-term interest rate responds instantaneously to shocks in domestic macroeconomic variables, including output and inflation measures (see, for example, Dungey and Pagan, 2000; Filis and Chatziantoniou, 2014).

We further assume that short-term interest rates, serving as a proxy for the policy instrument, have a contemporaneous effect on financial factors, while financial factors influence short-term interest rates with a lag. Restricting monetary policy to respond to the exchange rate and asset prices with a lag is debatable, as it suggests that the policymaker does not utilise all current information when designing monetary policy (Bjørnland, 2009). However, because most central banks do not meet monthly to set the policy rate and we are using monthly rather than quarterly data, we do not expect this to be a significant issue (see Bjørnland, 2009).

We follow the existing literature (e.g., Bjørnland 2009; Dungey et al. 2014; Dungey et al. 2019) in treating exchange rates and stock market indices as information variables that respond immediately to monetary policy shocks. This aligns with the market efficiency hypothesis, which states that asset prices adjust quickly to reflect all available information.

Following Bjørnland (2009) and Abouwafia and Chambers (2015), equity prices are contemporaneously endogenous to all other variables, indicating that the exchange rate responds to stock price shocks with a delay. This is consistent with the goods market hypothesis (e.g., Dornbusch and Fischer, 1980), which suggests that exchange rate fluctuations influence the competitiveness of exporting firms, thereby affecting their profits and firm value. Most firms in commodity-exporting countries (including some non-

exporting firms) are significantly affected by exchange rate fluctuations, as the U.S. dollar remains the dominant currency in global commodity markets.

The variables are therefore ordered as: *GEA*, *BAA*, *CXPI*, *GDP*, *inf*, *sr*, *rex*, and *spx*. From the relationship $A_0\varepsilon_t = u_t$, the short-run (zero) restrictions imposed imply:

$$\begin{bmatrix} a_{1,1} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{2,1} & a_{2,2} & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{3,1} & a_{3,2} & a_{3,3} & 0 & 0 & 0 & 0 & 0 \\ a_{4,1} & a_{4,2} & a_{4,3} & a_{4,4} & 0 & 0 & 0 & 0 \\ a_{5,1} & a_{5,2} & a_{5,3} & a_{5,4} & a_{5,5} & 0 & 0 & 0 \\ a_{6,1} & a_{6,2} & a_{6,3} & a_{6,4} & a_{6,5} & a_{6,6} & 0 & 0 \\ a_{7,1} & a_{7,2} & a_{7,3} & a_{7,4} & a_{7,5} & a_{7,6} & a_{7,7} & 0 \\ a_{8,1} & a_{8,2} & a_{8,3} & a_{8,4} & a_{8,5} & a_{8,6} & a_{8,7} & a_{8,8} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{GEA} \\ \varepsilon_t^{BAA} \\ \varepsilon_t^{CXPI} \\ \varepsilon_t^{gdp} \\ \varepsilon_t^{infl} \\ \varepsilon_t^{sr} \\ \varepsilon_t^{rex} \\ \varepsilon_t^{spx} \end{bmatrix} = \begin{bmatrix} u_t^{GA} \\ u_t^{GFR} \\ u_t^{CXP} \\ u_t^{1} \\ u_t^{2} \\ u_t^{3} \\ u_t^{4} \\ u_t^{5} \end{bmatrix}, \qquad (2.10)$$

where the u_ts are the structural disturbances, while the ε_ts denote the reduced form disturbances representing unexpected movements of each variable by construction.

Following the existing literature, we identify three types of underlying shocks that are assumed to drive fluctuations in commodity prices. *Global activity shocks (GA)* are an identified innovation in the global economic activity variable (IMF, 2012; Bjørnland and Thorsrud, 2016). A positive shock to global economic activity further boosts global economic activity and increases demand for all commodities, thereby raising commodity export prices (Kilian, 2009). Positive global activity shocks should also ease global financial conditions.

Global financial risk shocks (GFR) represent a significant innovation in the BAA spread, as identified by Akıncı (2013). This increase in global financial risk, seen in the widening of the BAA spread, is associated with rising interest rates and, consequently, higher inventory-holding costs, which dampen commodity demand (Frankel 2014). Additionally, worsening global financial conditions hamper global output, further exacerbating the decline in commodity demand. Weaker global demand for commodities puts downward pressure on commodity prices (Frankel, 2008; Juvenal and Petrella, 2024).

Commodity-specific price shocks (CSP) are an identified innovation in the CXPI that are contemporaneously unrelated to global economic activity and financial risks. These shocks, which raise global commodity prices on impact, are attributed to factors such as geopolitical tensions, natural disasters, expectations of future demand, or commodity-

specific supply pressures (see IMF, 2012; Charnavoki and Dolado, 2014; Bjørnland and Thorsrud, 2016). Since we focus on analysing the effects of the global shocks, we do not seek to identify the remaining structural disturbances (u^i for $i = 4,\ldots,8$).

Identifying a suitable monthly production indicator for all commodities is challenging. Additionally, several empirical studies indicate that supply-side commodity price shocks generally have minimal impact on commodity price changes and do not significantly influence fluctuations in real activity or financial markets (see, for example, Kilian, 2009; Kilian and Park, 2009; Hamilton, 2009; IMF, 2012; Basher et al., 2012; Bjørnland and Thorsrud, 2016). Therefore, we do not explicitly identify a global commodity supply shock.

2.4.1.4 Lag Selection

Selecting the correct lag length p is essential for accurately estimating impulse response functions. When data are limited, including too many lags can lead to overparameterization in each equation of the VAR model, increasing the risk of imprecise estimates. Conversely, choosing a smaller lag order can help preserve degrees of freedom, but it may also cause residual autocorrelation. Residual autocorrelation suggests that the model is not fully capturing the underlying dynamics of the data.

A reasonable practical constraint proposed by Ouliaris et al. (2016) is that the lag length should satisfy the $kp < T/3$ rule. Our baseline eight-variable SVAR model is estimated using 300 monthly observations, indicating a maximum lag length of 12. The Schwarz Bayesian criterion selects a lag order of $p=2$ for all countries, while the Akaike information criterion suggests lag orders ranging from 2 to 11. We observe that most models display residual autocorrelation when estimated with shorter lags, and some VAR models fail to meet the stability condition. By employing a bottom-up, sequential testing approach using the LM (Breusch-Godfrey) test for autocorrelation, we find that a lag order of $p=6$ reduces residual serial correlation in most country-specific SVARs.

2.4.2 Estimation

The A-B SVAR model in equation (2.9) is estimated using the maximum likelihood (ML) method (see Appendix B2 for a brief discussion of the ML estimation approach). For a VAR(p) model with an intercept, where $p>1$, the maximum-likelihood estimator is consistent and asymptotically normal even if unit roots are present. Standard Gaussian inference on individual slope parameters remains asymptotically valid (see Kilian and Lütkepohl, 2017).

This is because the reduced-form VAR slope parameters can be expressed as linear combinations of estimators of other parameter matrices, which are themselves asymptotically normal. SVAR model estimation is performed using EViews 12.

2.4.3 Inference

We use both structural impulse response functions (IRFs) and forecast error variance decompositions (FEVDs) to analyse the dynamic interactions among the variables. For these IRFs and FEVDs, asymptotically valid pointwise inference within VAR models can be performed using the delta method. There are concerns that the presence of unit roots and cointegration may complicate asymptotic inference, particularly for certain linear combinations of slope parameters that, although individually retaining their marginal Gaussian asymptotic distribution, have a joint variance-covariance matrix that is singular. This, however, is not a concern for structural impulse responses or structural forecast-error variance decompositions (see Kilian and Lütkepohl, 2017). Additional information on calculating IRFs and FEVDs is available in Appendices B.3 and B.4.

The IRFs are constructed from coefficients estimated with uncertainty, so they naturally contain sampling error. To address this, we construct confidence intervals for the impulse responses. Using the analytic asymptotic (delta) method, 95% confidence bands (roughly corresponding to ± 2 standard error bands) are constructed for structural impulse response functions. An IRF is considered statistically significant if zero does not fall within its confidence interval. For further details on the analytic asymptotic (delta) approach, see Appendix B.5.

The standard VAR model given by equation (2.6) captures the linear dependence of y_t on its own lags. The model is linear in both the autoregressive slope parameters and the lagged variables. This implies that the structural impulse response functions increase proportionally with the size of the structural shock. Furthermore, the impulse responses are symmetric with respect to positive and negative shocks, indicating that the response to a positive shock of a certain magnitude is an exact mirror image of the response to a negative shock of the same magnitude.

2.4.4 Model adequacy

Diagnostic tests assess whether the fitted VAR models adequately represent the data-generating process. The VAR model must satisfy the stability condition to apply standard

asymptotic theory. The necessary and sufficient condition for the weak stationarity of the VAR is that the (inverse) roots of the characteristic polynomial all lie within the unit circle.[5] If a VAR model does not satisfy the stability condition, impulse response functions fail to converge, rendering the standard errors invalid.

The VAR model assumes that the reduced-form innovation process ε_t is Gaussian white noise with no serial correlation. Portmanteau tests for low-order autocorrelation are not recommended for level VAR processes; therefore, we rely on the multivariate Breusch-Godfrey Lagrange multiplier (LM) test (Lütkepohl, 2013).[6] LM tests for residual autocorrelation indicate that the VAR(6) models still exhibit significant residual autocorrelation at the 5% significance level.

An examination of the VAR residuals' time series reveals several outliers. We therefore introduce country-specific dummy variables (termed impulse indicators), which take the value of one at time *t* and zero otherwise (see Ouliaris et al., 2018). An impulse dummy variable is included only if it alleviates residual autocorrelation, is significant in an equation at the 5% level, reduces the AIC for the VAR system, and supports the stability of the estimated VAR.

Tables 2.3a and 2.3b list the dummy variables used. Most of these dummy variables correspond to dates linked to various economic and political crisis events, such as the 1997–1998 Asian crisis, the 1998 Russian crisis, the 1998 Brazilian crisis, the 2001 dot-com bubble, the 2004 Iraq geopolitical tensions, the 2007–2009 GFC, the 2016 oil price and stock market declines, the 2018 US-China trade disputes, and other country-specific events.

At the 5% significance level, LM tests with 12 lags indicate that the impulse dummy variables help eliminate autocorrelation across all lags. Additionally, all the estimated VAR models are stable, as all the eigenvalues of the companion matrix lie within the unit circle. We do not consider tests for normality and conditional heteroscedasticity. According to Lütkepohl (2013), normality is not a necessary condition for the validity of statistical procedures in VAR and SVAR models. Furthermore, since a VAR model represents the conditional mean of the variables, unmodelled conditional heteroscedasticity in VAR innovations does not compromise the consistency of standard estimators of the VAR slope parameters.

[5] Put differently, all the roots of the characteristic equation (or determinantal matrix) are greater than 1 in absolute value. The modulus of the roots, if they are complex, must be greater than one.
[6] We rely on the Rao F-test version of the LM statistic in EViews 12 proposed by Edgerton and Shukur (1999) with better small sample properties.

2.5 Main Results

We begin by presenting and analysing the results of our baseline country-specific SVAR estimates. We utilise estimated impulse response functions (IRFs) to examine how our variables react to global shocks. The impulse responses (solid lines) to one-standard-deviation shocks in global variables, with their 95% (two-standard-error) confidence bands (red lines), are shown over 36 months to illustrate the short- to medium-term dynamic responses.[7]

The demeaned and detrended log-transformed variables (WIP, CXPI, real GDP, real exchange rate, and the real stock market index) are multiplied by 100 to express the impulse responses in percentages. The interpretation of the impulse response functions is therefore the dynamics of a variable around the data-specific steady state or trend extracted from the data (Dungey and Pagan, 2000). The vertical axis shows percentage changes in response to a one-standard-deviation structural shock.

How significant are global shocks in driving fluctuations in output and real equity indices? To answer this, we assess the relative importance of structural shocks in explaining variations in endogenous variables using forecast-error variance decomposition. We present the percentage contributions of these shocks over forecast horizons of up to 60 months.

2.5.1 Global variables

Before examining the effects of global shocks on real GDP and equity markets, we first review the responses of global economic activity (as measured by WIP), global financial conditions (proxied by the BAA spread), and the CXPIs.

World Industrial Production and BAA20YR spread. Figure 2.1 shows the impulse responses of WIP and BAA spread to global shocks. The responses shown in Figure 2.1 are simple averages of the estimated impulse responses from the eight country-wise SVARs.

The first column of Figure 2.1 shows that a one-standard-deviation increase in the world industrial production index, which boosts global economic activity, initially leads to a partially statistically significant easing of global financial conditions over the first five months. After nine months, the response of the BAA spread to the global activity (GA) shock turns positive, indicating a deterioration of global financial conditions, with this effect becoming statistically significant around the 15th month and persisting for slightly over a

[7] Longer time horizon impulses converge to zero. These are available upon request.

year. This deterioration in financial conditions is likely due to a general rise in price levels, prompted by increased global economic activity that boosts consumer confidence and spending, thereby raising demand for goods and services. Additionally, tightening monetary policy to combat inflationary pressures further tightens global financial conditions.

The second column shows that a one-standard-deviation increase in the BAA spread, which further worsens global financial conditions, is associated with a slowdown in global economic activity. The contraction in global real activity in response to the global financial risk (GFR) shock is significant over the first nine months.

A one-standard-deviation increase in CXPIs boosts global economic activity in the short term, although the effect is barely significant, aligning with Jacks and Stuermer (2020). CSP shocks are not correlated with either global activity shocks or global financial risk shocks, as previously noted. The CSP shock has a negligible impact on global financial conditions.

Country-specific commodity export prices. Figure 2.2 displays the CXPI impulse responses to the identified structural shocks across the sampled countries. An increase in global economic activity boosts demand for all commodities, thereby raising commodity prices (Di Pace et al., 2021). The first column of Figure 2.2 shows that the GA shock causes an immediate rise in all CXPIs, which is statistically significant for about 9 to 11 months in most countries. This excludes Russia, where significance persists for several years. Most CXPI responses peak within the first six to seven months. The largest peak responses to the shock are seen in the CXPIs of energy exporters Russia (around 4.3%) and Norway (around 3.3%). The response of New Zealand's CXPI, primarily an agricultural exporter, has the smallest peak (about 1.2%), followed by the metals exporter Chile (approximately 1.7%). The peak responses of the CXPIs across the remaining countries range from 2.3% to 2.8%.

The GFR shock leads to an immediate and significant decline of all CXPIs, as shown in the second column of Figure 2.2. When global financial conditions tighten, credit becomes more expensive, reducing consumption and investment, raising inventory-holding costs, and lowering demand for commodity exports, resulting in a decline in global commodity prices (Miranda-Agrippino and Rey, 2022; Juvenal and Petrella, 2024). CXPIs typically reach their lowest point within about three months after the shock and remain statistically significant for approximately six months in most countries. The largest CXPI decline occurs in Russia (around 3.5%), followed by Norway (around 2.8%). In most cases, the negative reactions to CXPIs peak between 1% and 2% in absolute terms.

The last column of Figure 2.2 indicates that all CXPIs react immediately to the CSP shock. In most countries, the positive response stays statistically significant for 9 to 15 months, except in Chile, where it remains significant for more than two years.

The CXPI forecast error variance decomposition results shown in Table 2.4 indicate that the GFR shock generally dominates the GA shock at forecast horizons of up to three months in most countries. At longer horizons, the GA shock tends to dominate the GFR shock. The exception is Chile, where the GFR shock continues to account for a larger share of CXPI variability even at horizons exceeding 36 months. Among domestic variables, innovations to the real stock market index (Brazil and Chile), real GDP (Australia and South Africa), inflation (Chile and Norway), and the real exchange rate (Brazil, Canada, and Norway) have modest contributions to the variability in their respective CXPIs.

2.5.2 The effects of global shocks on real GDP

Structural Impulse Responses. Rising global commodity prices improve an exporting country's terms of trade, which, through the income effect, should boost purchasing power, enabling higher consumption levels and encouraging investment in the commodity sector and related industries. This could potentially benefit other parts of the economy, leading to increased real activity (see Aslam et al., 2016). However, there is a broad consensus that the economic impact on commodity exporters depends on the specific cause of the change in commodity prices.

The first column of Figure 2.3 displays the effects of a one-standard-deviation shock to global economic activity on real GDP. The GA shock has statistically significant expansionary effects on real GDP across all EMEs and in the AEs Australia and Canada. The expansionary impact is immediate and statistically significant for the first 17 months in Brazil and for approximately five years in Russia. The positive response in Chile and South Africa is significant from the second month until about the 17th month. The real GDP responses in Australia and Canada are statistically significant for the first 24 and 14 months, respectively. The response in Norway is only partially significant during the initial 14 months. GA shocks are estimated to have an insignificant positive effect on New Zealand's real GDP. The response turns negative a year after the initial impact, which aligns with Fornero et al. (2016).

The positive impact of the GA shock is greater in EMEs. Among the countries sampled, Russia exhibits the largest peak effect, at roughly 0.30%, which occurs 13 months

after the shock. Russia's aggregate output response supports the observation by Juvenal and Petrella (2024) that countries experiencing a more sustained rise in export prices, driven by increased global economic activity, tend to see larger gains in real GDP. The maximum effects are 0.21% in Brazil (after 10 months), 0.11% in Chile (after 7 months), and 0.11% in South Africa (after 10 months). The peak percentage change in Australia's real GDP is around 0.05%, occurring within the first four months. In Canada and Norway, the response peaks at approximately 0.07% after 9 and 10 months, respectively.

The impact of a one-standard-deviation shock to the BAA spread is statistically insignificant in most countries (see the second column of Figure 2.3). The exception is Brazil, where the contractionary effect of a GFR shock on real GDP is statistically significant from the second month after impact until about the tenth month. We do not find evidence indicating that real economic activity is an important channel of transmission for the GFR shock. This is somewhat at odds with studies such as Akıncı (2013), Choi (2018), and Yildirim (2022), which find that the shock has a significant negative effect on output in EMEs.

The impulse responses shown in the third column of Figure 2.3 demonstrate the effects of a one-standard-deviation shock to country-specific commodity export price indices. The CSP shock has a minimal impact on output in most of the countries analysed. This finding aligns with Bjørnland and Thorsrud (2016), who observe that the structural shock does not substantially influence Norway's real GDP. Exceptions include Russia, where the shocks cause a significant expansionary effect from the second month through about the eleventh month after the impact, and Chile, where the effect becomes significant from the fifteenth month and lasts for roughly a year. According to Cunningham and Smith (2019), increases in commodity prices driven by commodity-specific shocks (such as those causing temporary supply disruptions) generally have short-term effects on export, investment, and consumption outlooks, thereby posing a minor influence on real economic activity.

Variance Decomposition. Table 2.5 shows the forecast-error variance decompositions for real GDP. The important role of the global activity shock in causing output variations across countries is evident. In most cases, the contribution of the GA shock exceeds that of other shocks (except for own shocks) in explaining output fluctuations, especially over short- to medium-term forecast horizons.

The percentage contribution of the GA shock to output variation is highest in Russia across all forecast horizons, reaching about 52% after 60 months. Brazil follows, with the

shocks' maximum contribution of approximately 41% at the one-year horizon. The shock also significantly influences the variance of output forecast errors in South Africa and Chile, accounting for nearly 20% and 35%, respectively, at the one-year forecast horizon. The variance decomposition assigns roughly 25% of output fluctuations to the GA shock for forecast horizons beyond 36 months in Australia and around the 12-month horizon in Canada. In Norway, the shock's impact is relatively modest, explaining at most about 12% at the 12-month horizon. Although the shock's explanatory power for New Zealand's output fluctuations is minor at short-term forecast horizons, it becomes more significant at longer-term horizons.

Consistent with the IRF results, the contribution of the GFR shock to real GDP variation is generally minimal in most countries, typically not exceeding 4% over the 60-month horizon. Brazil and New Zealand are somewhat exceptions, where the proportion explained by the shock eventually reaches about 10% and 11% at the 12- and 24-month forecast horizons, respectively. Our findings differ from those of Akıncı (2013) and Choi (2018), who argue that global financial risk shocks play a significant role in fluctuations in emerging-market output. Epstein et al. (2019) find a very small proportion of FEVD associated with innovations in global financial risk in EMEs, but, conversely, a substantial contribution of the shock to output fluctuations in advanced economies. Differences in the findings may arise because these panel VAR-based studies do not include measures of global economic activity and commodity prices.

The share of the output forecast error variance explained by the CSP shock is also small (less than 4%) in most countries, supporting the IRF evidence. However, the contributions increase slightly to at most 8% and 9% after 6 months in Canada and Russia, respectively, and eventually peak at 15% at the 5-year forecast horizon in Chile.

Global shocks seem to play a larger role in fluctuations in real GDP in EMEs than in AEs. The last column of the FEVDs in Table 2.5 shows that Russia and Brazil are the most susceptible to external shocks, with external shocks outweighing domestic ones at forecast horizons beyond 6 months in Russia and between 6 and 24 months in Brazil. The combined contribution of these three shocks peaks at approximately 52% and 61% at the one-year horizon, respectively. Table 2.1 indicates that Russia relies heavily on oil and gas exports, which account for a significant share of its GDP. The strong influence of global economic growth on energy prices, sanctions, and heightened geopolitical risks makes the Russian economy susceptible to external shocks. Brazil's economy is also vulnerable to external shocks due to structural weaknesses, such as a complex tax system, a large informal sector,

poor infrastructure, a lack of a sound fiscal framework, and a challenging political environment (ECB, 2016).

Together, global shocks have the smallest impact on Norway's output fluctuations, with a maximum contribution of around 17% at the 24-month horizon. Pieschacón (2012) suggests that Norway's fiscal policy shields its economy from commodity price shocks, thereby reducing the effect of external shocks. On average, the combined influence of global factors is greater in emerging market economies (EMEs) than in advanced economies (AEs), as summarised in Figure 2.5.

We find that inflation innovations have a modest effect in Brazil, peaking at about 14% in the medium term, and in Chile, reaching 18% over the long term. The impact of stock market shocks is especially significant at medium to longer forecast horizons in EMEs. The contribution of stock market innovations peaks at around 41% in Brazil and between 16% and 20% in Chile, Russia, and South Africa.

2.5.3 The effects of global shocks on equity markets

Structural Impulse Responses. The first column of Figure 2.4 shows the effects of a one-standard-deviation increase in the measure of global economic activity on equity markets. Results show that GA shocks have a significant positive impact on equity prices in Australia, Brazil, Canada, Norway, and South Africa. A positive shock to global economic activity generally increases commodity demand, which in turn raises commodity export prices. This constitutes a positive terms-of-trade shock for commodity exporters, likely boosting growth expectations, reducing uncertainty, and enhancing investor sentiment, thereby raising stock prices.

The stock market's impact response to GA shocks is statistically significant only in Australia, the largest of the sampled countries (approximately 0.8%). Estimates indicate that Brazil's equity market shows the largest peak response, at roughly 4.4%, about eight months after the impact, with the effect gradually returning to baseline. The hump-shaped responses peak at around 3% within four months in Australia, Canada, and South Africa, and at approximately 3.8% in Norway, after which the effect gradually diminishes.

In contrast, the second column of Figure 2.4 illustrates that equity prices decrease following an unexpected one-standard-deviation shock to the BAA spread. Tighter global financial conditions, possibly stemming from rising risk aversion or contractionary monetary policy in key advanced economies, can heighten uncertainty, increase capital outflows, and

raise risk premiums in local economies. This effect can be amplified for commodity exporters as commodity prices decline further, leading to downward revisions in earnings forecasts and falling stock market values.

GFR shocks have a statistically significant immediate negative effect on all equity markets. The stock market's negative response reaches its lowest point within two to six months after the impact. In Canada, Chile, Norway, and Russia, this negative response becomes statistically insignificant after approximately six months, whereas it remains significant for about 12 months in Brazil, 15 months in Australia and South Africa, and 18 months in New Zealand.

The negative response of equity markets on impact is more pronounced in the EMEs Brazil and Russia, with the largest immediate falls of approximately 3.8% and 4%, respectively, and further declines reaching troughs of about 5.7% and 5.5% after six and five months, respectively. Regarding AEs, the negative stock market response is more significant in Norway, falling by about 2.9% on impact and hitting a trough of around 3.9% within two months. The New Zealand stock market, an agricultural exporter, shows the smallest decline, about 1.7%, on impact. For the remaining countries in the sample, results indicate equity markets decline by between 2.2% and 2.7%.

Our results align with recent theoretical and empirical literature that emphasises the financial channel as a key transmission mechanism for global financial conditions (Akıncı and Queralto, 2021; Miranda-Agrippino and Rey, 2022). Horvath and Yang (2024) demonstrate that equity prices are a powerful conduit for global financial risk shocks affecting macroeconomic activity. Our findings are consistent with Yildirim (2016), who shows that emerging-market equity prices decline in response to global financial risk shocks. Basher et al. (2012) also find that increased financial stress is linked to falling real oil prices, which subsequently lead to reduced real economic activity and declining stock prices in oil-exporting emerging markets.

The rise in stock markets following a one-standard-deviation increase in the CXPI is statistically significant on impact across all countries. In most countries, the instantaneous increase in stock market values ranges from 1.1% to 1.7%, except in New Zealand, where it is around 0.5%. However, the statistical significance of this positive response is usually short-lived, lasting between one and five months in most countries. The exception is Chile, where the positive stock market response is sustained and statistically significant for over three years. The relatively modest impact of CSP shocks on equity markets can be attributed

to the observation that these shocks tend to be idiosyncratic (for example, adverse weather disrupting supply), unlike global demand shocks that drive sustained increases in commodity prices.

Variance Decomposition. Table 2.6 displays the stock market forecast-error variance decompositions. The results show that the GFR shock is the most influential external shock impacting stock market fluctuations. The shock's impact is greatest at the one-month-ahead forecast horizon in Australia, Canada, and Norway, accounting for approximately 29%, 29%, and 33%, respectively. Although the shock's contribution tends to decrease over time in Canada and Norway (eventually reaching around 10% after 60 months), it remains considerable at longer forecast horizons for the Australian equity market, contributing nearly a quarter after 60 months. The influence of the GFR shock is initially modest in New Zealand (about 15%), peaking at 23% at the 24-month forecast horizon. In Brazil and Chile, the maximum contributions are 23% and 24%, respectively, at the one-month-ahead horizon. It peaks at around 15% and 19% at the three- and twelve-month horizons for Russia and South Africa. Overall, the GFR shock tends to explain a larger share of stock market fluctuations in developed economies compared to emerging markets.

Global activity shocks are of secondary importance compared to GFR shocks. Over the 60-month forecast period, the impact of the GA shock on equity market fluctuations in Australia, Canada, and Norway is modest, with peak values of 17%, 18%, and 19% at the six-month mark, respectively. Its relevance for the South African stock market is especially significant at longer forecast periods, accounting for about a fifth at five years. In Chile, New Zealand, and Russia, the shock's contribution is initially very small in the short- to medium term but eventually increases to 11%, 15%, and 17%, respectively, at the five-year horizon. In Brazil, the contribution only rises to around a tenth at horizons exceeding 12 months.

Consistent with IRFs, the CSP shock is the least influential external shock for equity market variability, contributing small fractions (at most 8%) in most countries. The exception is Chile, where it contributes about 15% by the 12-month forecast horizon, peaking at 30% by the 36-month forecast horizon.

On average, the three identified global shocks collectively account for a greater share of stock market volatility in AEs than in EMEs, especially at horizons up to about 36 months (Figure 2.5). Together, global shocks explain nearly 50% of monthly equity index fluctuations in Australia and Norway, and just over 40% in Canada by the fourth month. The peak contributions of global shocks in Chile (44%), New Zealand (37%), Russia (29%) and

South Africa (42%) occur after 60 months. This finding aligns broadly with the literature, which argues that global forces are likely to play a more important role in driving risky asset prices worldwide (Yildirim, 2016; Miranda-Agrippino and Rey, 2022). The lower sensitivity of EM stock markets suggests they are relatively insulated from global shocks. Recent research suggests that decoupling from advanced economies has made some EMEs less vulnerable to external shocks than AEs over recent decades (see, for example, Kose et al., 2012; Hallam, 2022).

Innovations in some domestic variables also significantly contribute to stock market fluctuations. Table 2.6 shows that exchange rate shocks account for a substantial part of the variance in stock prices in most countries, with contributions often comparable to those of own shocks. Exceptions are the energy exporters Norway and Russia, where exchange rate shocks seem to have relatively smaller effects. Shocks to real GDP have considerable predictive power for stock market variance in Russia at horizons beyond three months and in Australia, New Zealand, and South Africa at horizons beyond six months, with maximum contributions ranging from 19% to 31%. Inflation and interest rate shocks are most relevant in Norway, each accounting for about 20% of the variance in the 24-month forecast error.

2.6 Sensitivity analysis

We assess the robustness of our baseline results using the following alternative specifications: (i) an alternative measure of economic activity; (ii) an alternative measure of global financial risk; (iii) quarterly data; (iv) a shorter sample period; and (v) non-detrended data. Figure 2.16 compares the stock market impulse responses to global shocks under the alternative specifications. Overall, the robustness analysis confirms the baseline results, with the main messages remaining unchanged. We briefly discuss each robustness exercise below, along with the corresponding figures in Appendix D.

2.6.1 Robustness to an alternative measure of output

A concern with using interpolated real GDP, as Kilian (2009) cautions, is that it can induce spurious dynamics. We therefore assess the robustness of our results by re-estimating the models using the industrial production index (the employment rate for New Zealand) as an alternative to the interpolated real GDP.

Figure 2.6 shows the impulse responses of the industrial production index (IPI) to global shocks. The estimates indicate that the GA shock has notable expansionary effects on

the IPI across all emerging market economies, but only in Canada among advanced economies. This aligns with our baseline finding that the impact of GA shocks on real output appears stronger in the sampled EMEs than in AEs. Consistent with the baseline SVAR results, the GFR shock generally has negligible contractionary effects on economic activity in most countries. Exceptions are Brazil, as in the baseline, and Russia, where the IPI contraction following GFR shocks is statistically significant from the second month after impact and persists for about 10 months. The effect of the CSP shock on IPI tends to be muted, in line with the baseline.

The stock market IRFs in Figure 2.7 and the associated FEVDs in Table 2.8 demonstrate that the global activity shock exerts stronger effects on the stock markets of Australia, Canada, Norway, and South Africa, whereas its impact on Brazil is weaker. The equity market response to the GA shock in Russia is statistically significant for approximately five months, beginning in the third month after the shock, in contrast to the baseline findings. Impulse responses of stock markets to global financial risk and commodity-specific price shocks remain largely consistent with the baseline estimates. The forecast-error variance contributions of the GFR shock to equity market variability at horizons beyond three months are marginally lower in Australia, New Zealand, and South Africa. Despite slight variations in the dynamic responses to the global activity shock, the sensitivity test results remain consistent with the baseline conclusions.

2.6.2 Robustness to an alternative measure of global financial risk

The VIX index, an implied volatility index of the U.S. equity market, is widely regarded as an indicator of global financial risk (see Akinci, 2013; Yildirim, 2022). Rey (2015) underscores the importance of the VIX in shaping international capital flows, credit growth, and the valuation of risky assets. We re-estimate the VAR system using the VIX as an alternative measure of global financial risk. The log-transformed VIX is demeaned and detrended prior to estimation.

The real GDP responses to GA and CSP shocks reported in Figure 2.8 remain largely unchanged relative to the baseline. We find that a positive VIX shock (indicating a deterioration in global financial conditions) elicits responses similar to those in the benchmark analysis. The stock market impulse responses to the three global shocks, reported in Figure 2.9, are identical to those in the baseline (see Figure 2.4). These results align with Yildirim (2016) and Horvath and Zhong (2019), who report a significant negative response of EMEs' equity prices to a global financial risk shock proxied by the VIX index.

The variance decompositions in Tables 2.9 and 2.10 also reinforce the robustness of our baseline results. Overall, this experiment shows that our main findings remain robust to an alternative measure of global financial risk.

2.6.3 Subsample analysis: 2003 to 2019 period

The baseline SVAR estimates are based on a sample period spanning January 1995 to December 2019. Global commodity prices surged markedly from 2003, peaking in 2008, primarily due to unanticipated strong commodity demand driven by the global business cycle (Kilian, 2009). The financialization of commodity markets, a period from the mid-2000s characterised by a sharp increase in commodity futures trading, is also believed to have considerably contributed to the commodity price boom. Given the importance of this period, we examine whether the baseline results remain consistent with a shorter sample starting in January 2003.

Figure 2.10 shows a significant short-term expansionary response of real GDP to the GA shock in Australia, Canada, Brazil, Russia, and, to a lesser extent, South Africa. Notably, New Zealand's real output response to the global activity shock, initially negligible, becomes negative after four months and persists for several months, remaining statistically significant from the ninth month until around the thirtieth month. A contractionary response is also observed in Norway after fifteen months, though it is barely significant. Contrary to the baseline findings, GFR shocks exert a strongly statistically significant contractionary impact on real GDP in Canada and New Zealand. The CSP shock appears to have no notable effect on output across the countries examined.

The variance decomposition of the output forecast error shown in Table 2.11 supports the IRF findings, suggesting that the GFR shock has strong predictive power for output fluctuations in Australia, Canada, Brazil, Russia, and New Zealand. The explanatory power of this shock is moderate in South Africa (up to 14%), but less than 10% in Chile and Norway. As with the baseline SVAR results, the analysis confirms the CSP shock's limited predictive ability across the sampled countries, except in Brazil.

The responses of stock markets to global shocks, as shown in Figure 2.11, largely correspond with our main SVAR findings. Notably, the equity market response to the GA shock in New Zealand turns negative after eight months, with statistical significance beginning fourteen months post-impact and continuing for about a year. The CSP shock

generally has a marginally stronger effect across most countries, except for New Zealand and South Africa.

The stock market variance decompositions shown in Table 2.12 align with the main finding that the GA shock has a small impact on stock market volatility in Chile and Russia. The FEVDs corroborate the IRF results, indicating that the CSP shock's contribution to equity market fluctuations is slightly greater for most countries, except New Zealand and South Africa.

This robustness check demonstrates that, on average, external shocks have a notably larger combined impact on output fluctuations in AEs compared to EMEs. For instance, in Canada, the effect peaks at about 68% at the 12-month forecast horizon. The influence of global shocks exceeds 60% in New Zealand at horizons beyond 24 months, while in Australia, it reaches nearly 40% after 60 months. Conversely, Chile's contribution is the lowest, with a maximum of 12% of output variance over the 60-month forecast horizon considered. Literature often attributes Chile’s economic resilience to its countercyclical fiscal policies, which are credited with reducing GDP volatility throughout the 2000s despite a 400% increase in copper prices between 2003 and 2008 (Céspedes et al., 2014).

The sensitivity test confirms the initial finding that, on average, global shocks exert a greater influence on stock market volatility in AEs than in EMEs. The estimates suggest that, collectively, the contribution of external shocks peaks at around 50% at the six-month forecast horizon for Australia and Canada, at 60 months for New Zealand, and at one month for Norway.

2.6.4 Robustness to detrending

In the relevant SVAR literature, it is common to include a linear trend in the model (as in Bjørnland, 2009) or to employ detrended data (such as in Dungey et al., 2014; da Silva Souza and Fry-McKibbin, 2021). The resulting model characterises macroeconomic outcomes as transitory deviations from a deterministic trend. Although the VAR in levels is asymptotically valid even with true cointegration, Kilian and Lütkepohl (2017) caution that finite-sample bias can be substantial, particularly when a deterministic time trend is incorporated. Sims (1987) recommends omitting the deterministic trend to prevent potential model misspecification and overfitting in small samples (see Kilian and Lütkepohl, 2017).

We re-estimate the six-lag SVAR model in levels using non-detrended data, including an intercept, and apply the same identifying restrictions. All variables are expressed in log

terms, except for the BAA spread, short-term interest rates, and inflation, which stay in percentage units. Figures 2.12 and 2.13 display the impulse responses of real GDP and the equity market, respectively, based on non-detrended data. Although the impulse response functions are mostly similar across specifications, in some cases, the real GDP IRFs take longer to return to baseline (longer-horizon results are available upon request). Notably, the response of real GDP to the GA shock in Brazil (Russia) remains significant for over five years (21 months), whereas it lasts less than two years (about 60 months) when using detrended data. IRFs (Figure 2.11) and FEVDs (Table 2.13) suggest that the estimated impact of the CSP shock on real GDP in Russia (Chile) is more pronounced (or negligible) than when estimated using detrended data. Overall, these results indicate that the key conclusions of the baseline model generally remain valid.

2.6.5 Robustness to data frequency

Most small open-economy SVAR studies employ quarterly data (Peersman and Van Robays 2012; Fornero et al. 2016; Epstein et al. 2019). We re-estimate our country-specific small open-economy SVARs using quarterly data, with a lag order of $p=2$. The data are transformed before estimation, following the baseline approach, and the variable order remains unchanged to align with the quarterly SVAR framework of Fornero et al. (2016). The impulse response functions for real GDP and the stock market are shown in Figures 2.14 and 2.15, respectively.

The findings demonstrate that stock market reactions to the GA shock are significant across all studied countries. This significance persists for about five quarters in Australia, Brazil, Canada, and Norway, and for 2 to 3 quarters in Chile, Russia, and South Africa. The impact of the GFR shock is quite similar to that observed when using monthly data. Although stock market responses to the CSP shock mainly align with baseline estimates across countries, they are initially insignificant in Australia, New Zealand, and Russia. The effects of global shocks on real output generally correspond to those found in the baseline monthly SVAR models.

Tables 2.15 and 2.16 show the output and stock market FEVDs from the quarterly SVAR model. The analysis confirms that (i) shocks to global activity have a more significant impact on EME real output than on AEs, (ii) global financial risk and commodity (specific) price shocks, with some exceptions, generally have negligible effects, and (iii) the predictive power of external shocks for output variability is stronger in EMEs than in AEs. The

maximum combined contribution of external shocks to output variability in South Africa (27%) and Canada (44%) matches estimates from Houssa et al. (2023).

The analysis confirms the initial finding that external shocks have a greater impact on AE stock market fluctuations compared to EME stock markets. External shocks' contribution to equity market fluctuations exceeds that of domestic shocks across all forecast horizons in Australia, reaching about 56% after eight quarters. In Canada and Norway, this external influence is more pronounced at short-term horizons, peaking at approximately 60% and 72%, respectively, at the one-month forecast. Overall, this robustness check strengthens the initial conclusions regarding the influence of global shocks on both output and stock market performance.

2.7 Concluding remarks

This chapter examines the macroeconomic and stock market impacts of global shocks on small open economies that rely heavily on commodity exports. We focused on eight net commodity exporters: Australia, Brazil, Canada, Chile, New Zealand, Norway, Russia, and South Africa.

It is well understood that the real price of commodities is determined endogenously in global markets, influenced by the same economic factors affecting macroeconomic aggregates and stock prices. Therefore, it is crucial to consider reverse causality. Additionally, recent studies emphasise the need to consider the underlying causes of commodity price fluctuations when assessing their effects (Kilian 2009; Kilian and Park, 2009). To this end, using a monthly dataset covering January 1995 to December 2019, we estimate country-specific structural vector autoregressions (SVARs) that incorporate measures of global economic activity, global financial conditions, and country-specific commodity export price indices to reflect global commodity market conditions relevant to each commodity-exporting country. Using short-run identification restrictions, we identify three global shocks: global activity, global financial risk, and commodity-specific price shocks.

Results indicate that the identified global shocks impact stock markets and macroeconomic performance differently across countries, highlighting considerable heterogeneity. The global activity shock generally loosens global financial conditions in the short term and increases commodity export prices. We find that the shock significantly boosts real output in most of the sampled countries, except New Zealand. Additionally, the

shock significantly raises equity market values in Australia, Canada, Norway, and South Africa, and to a lesser degree, in Brazil.

A deterioration in global financial conditions, which amplifies financial risks worldwide, diminishes overall economic activity and reduces commodity prices. Our analysis indicates that global financial risk shocks generally have little to no impact on total economic output across the sampled countries. Nonetheless, these shocks cause significant contemporaneous declines across all stock markets. Commodity (specific) price shocks further raise global commodity prices but have only a minor effect on global economic activity and an insignificant impact on global financial conditions. These shocks are found to have negligible effects on real output in most countries, with some exceptions such as Chile and Russia. Although stock markets initially react positively to commodity (specific) price shocks, this response is brief and only briefly significant in most cases.

Variance decompositions indicate that, among external shocks, global activity shocks tend to have a greater impact on output fluctuations, particularly in the sampled emerging economies. In contrast, global financial risk and commodity (specific) price shocks generally appear inconsequential in most cases. Global financial risk shocks have a stronger influence on equity market fluctuations, particularly in developed economies, while global activity shocks are of secondary importance, and commodity price shocks have a negligible effect. The overall impact of global shocks on output fluctuations is relatively larger in the emerging economies considered, whereas collectively, they contribute a higher proportion to stock market fluctuations in developing economies.

This chapter's findings can inform international investors who are considering including stock markets from commodity-exporting emerging and developed economies in their portfolios. Our analysis suggests that adjusting portfolios appropriately after global commodity market shocks requires understanding the factors driving commodity price changes. The varied responses to specific shocks and differences across countries offer valuable opportunities for diversification.

The literature has extensively examined how changes in asset prices influence household wealth, consumption, and the wider economy. Policymakers contend that stock market fluctuations can impact real economic activity through a consumption-wealth effect. Our analysis enhances understanding of how various global shocks affect output and stock markets, which is crucial for predicting consumption and overall economic trends, assessing

risks to the economic outlook, and devising appropriate macroeconomic policies to ensure macroeconomic and financial stability (Cooper and Dynan 2016).

Commodity exporters, especially emerging economies, can maintain a strong net foreign asset position, including foreign-currency reserves, to improve their resilience against adverse global shocks (UNCTAD, 2023). Accumulated foreign currency reserves can act as a buffer against negative export income shocks, sudden stops in international capital flows, or foreign currency liquidity crises. Additionally, strong institutions and robust policy frameworks are vital to economic resilience in the face of adverse global shocks. Diversification strategies, such as developing alternative sectors (e.g., manufacturing and services), can also reduce vulnerability to adverse external shocks (UNCTAD, 2023).

Finally, our study has inherent limitations that could be addressed in future research. Although structural VAR analysis offers valuable insights into country-specific output and stock market responses to structural shocks, a limitation of this approach is that several other significant determinants of macroeconomic and stock price performance are not incorporated into the empirical framework. For instance, heterogeneity in responses to shocks may stem from differences in institutional quality and policymaking. Therefore, future research using panel data methods and including additional variables could also provide useful insights.

2.8 Tables and Figures

2.8.1 Tables

Table 2.1 Commodity exports as a share of merchandise exports and GDP (2012–14)

	Australia	Brazil	Canada	Chile	New Zealand	Norway	Russia	South Africa
% share of merchandise exports	85	63	48	86	76	77	77	56
Agriculture	17	40	15	30	70	10	6	13
Energy	27	8	22	1	2	61	64	10
Minerals	40	15	11	55	4	6	7	33
% share of GDP	13.3	6.3	12.3	22.8	14.9	21.2	18.7	14.4

Source: UNCTAD (2019)

Table 2.2 Data description and sources

Variable	Country	Frequency	Source
World Industrial Production (WIP) Index	International	Monthly	Baumeister, C. and J.D. Hamilton (2019) https://sites.google.com/site/cjsbaumeister/datasets
Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity	U.S.	Monthly (average)	Federal Reserve of St.Louis
CBOE Volatility Index: VIX, Index, Monthly, Not Seasonally Adjusted	U.S.	Monthly (average)	Federal Reserve of St.Louis
Commodity Export Price Index	All countries	Monthly	IMF Data https://data.imf.org/?sk=2cddccb8-0b59-43e9-b6a0-59210d5605d2
3-Month Interbank Rates	Australia, Canada, New Zealand, Norway, South Africa	Monthly	Organisation for Economic Co-operation and Development (OECD) https://data.oecd.org/interest/short-term-interest-rates.htm
Deposit Rate	Brazil, Chile	Monthly	IMF - International Financial Statistics
Interbank Rate - Overnight Interbank Credits	Russia	Monthly	The Central Bank of the Russian Federation
Gross Domestic Product (GDP) by Expenditure: Constant Prices	All countries	Quarterly	Federal Reserve of St.Louis
Consumer Price Index (% year-on-year)	All countries + U.S.	Monthly	DataStream
Consumer Price Index (level)	All countries	Monthly	DataStream
Nominal Exchange Rate	All countries	Monthly (average)	OECD
MSCI Price Index	All countries	Daily	DataStream
Retail Sales	All countries except New Zealand		DataStream
Unemployment	New Zealand	Monthly	Federal Reserve of St.Louis

Notes: Quarterly observations for the world industrial production index, BAA spread, commodity export prices, interest rates, stock market indices, and exchange rates have been constructed by averaging the series over the quarterly time interval.

Table 2.3a SVAR Dummy Variables

Australia	Brazil	Canada	Chile	Norway	New Zealand	Russia	South Africa
			Baseline SVAR				
2000m11	1996m07	2001m11	1997m12	1997m01	1996m07	1995m12	1997m11
2001m10	1997m07	2004m05	1998m03	1999m06	1998m09	1997m11	2008m02
2004m05	1997m011	2009m07	1999m04	2003m01	2007m08	1998m01	2009m02
2008m04	1998m01		2005m09	2003m08	2011m10	1999m03	2015m01
2011m04	2001m01		2008m12	2007m04		1999m09	
	2002m11		2011m07	2007m09		2000m12	
	2004m05			2008m03		2007m01	
	2009m02			2009m11		2008m01	
				2011m01		2009m07	
				2014m12		2010m05	
						2015m08	
			Robustness - Industrial Production Index				
1996m03	1995m09	2004m02	1996m05	1997m01	2002m06	1995m12	2001m05
2001m10	1996m01	2006m09	1997m12	1999m06	2008m02	1996m05	2004m06
2009m09	1996m12	2009m07	1998m02	2000m05	2009m12	1996m12	2009m04
2011m08	1997m03	2010m03	1999m04	2003m01	2010m05	1997m11	2009m06
	1997m11	2015m01	2005m09	2003m04	2010m10	1999m09	
	1998m03		2007m11	2003m08	2012m01	1999m11	
	1999m02		2009m03	2007m11	2013m03	2000m02	
	2003m04			2009m03	2015m11	2000m05	
	2004m05			2009m11	2016m09	2007m01	
				2010m12		2008m01	
						2010m05	
						2011m08	
						2015m08	
			Robustness: VIX				
2000m11	1997m07	1996m12	1998m02	1999m06	2003m04	1995m12	1996m08
2001m07	1997m11	2001m04	2001m02	2003m01	2007m08	1996m05	2006m06
2001m10	2004m05	2001m11	2001m08	2007m09		1996m12	2006m11
2008m04	2009m02	2004m01	2005m09	2015m07		1997m11	2008m05
2011m04	2016m03	2004m05	2007m04			1999m09	2018m04
	2018m12	2008m04	2011m08			1999m11	
		2015m01				2000m02	
						2000m05	
						2003m03	
						2007m01	
						2008m01	
						2010m05	
						2011m08	
						2015m08	

Notes: m denotes month and q denotes quarter

Table 2.3b SVAR Dummy Variables

Australia	Brazil	Canada	Chile	Norway	New Zealand	Russia	South Africa
			Robustness: 2003-2019 subsample				
2008m12	-	2006m09	2005m09	2006m04	2011m04	2009m07	2008m05
2009m09		2007m10	2006m05	2007m09	2004m01	2016m01	2006m06
2010m01		2009m01	2009m04	2011m01	2009m03		2007m02
2011m01		2009m06	2011m08	2016m01			2018m04
2015m02		2015m11	2013m06				2015m12
2016m01			2014m01				
2016m05			2015m08				
			Robustness: Quarterly data				
2009q2	2000q2	2003q1	2007q1	2006q4	2006q4	1995q4	2002q4
	2002q3		2007q4	2009q3	2010q1	1996q2	2015q3
			2009q3			1999q1	
			2010q1			2000q2	
						2008q1	
						2009q3	
			Robustness: Non-detrended data				
2000m11	1999m02	2001m11	1998m03	2003m01	2011m10	2014m11	1997m11
2004m05	1997m07	2009m07	1999m04	1997m01	2007m08	1998m02	2008m02
2011m04	1997m11	2004m05	2005m09	2007m09		2009m07	2009m02
2001m10	1998m01		2007m10	2007m04		1995m12	2015m01
2008m04	2001m01		2008m04	1999m06		2011m08	
	2004m05		2011m07	2003m08		1997m11	
			2015m08	2011m01		1999m03	
				2009m11		1999m09	
				2014m12		2000m02	
				2008m03		2000m05	
						2001m07	
						2007m01	
						2008m01	
						2010m05	

Notes: m denotes month and q denotes quarter

Table 2.4 CXPI Forecast error variance decompositions

	Period	*WIP*	*BAA*	*CXPI*	*GDP*	*INFL*	*SR*	*REX*	*SPX*
	1	6	13	81	0	0	0	0	0
	3	16	15	67	0	0	1	1	1
Australia	***6***	22	12	54	1	0	1	5	4
	12	23	10	44	8	1	3	8	3
	24	17	10	40	19	1	3	7	3
	36	15	10	40	22	1	4	6	2
	60	13	13	34	27	1	4	5	3
	1	2	8	90	0	0	0	0	0
	3	8	15	76	0	0	0	1	0
Canada	***6***	18	12	65	0	1	0	3	1
	12	18	9	48	1	2	2	18	1
	24	15	7	36	4	3	3	27	6
	36	14	7	32	4	4	3	27	10
	60	14	7	27	9	4	4	26	9
	1	2	6	92	0	0	0	0	0
	3	7	14	76	1	1	0	0	0
New	***6***	15	13	66	0	2	1	3	0
Zealand	***12***	18	11	53	2	4	2	9	0
	24	15	11	43	7	7	5	8	4
	36	14	12	40	8	8	5	9	5
	60	15	12	37	8	8	5	11	5
	1	2	6	92	0	0	0	0	0
	3	6	15	75	0	1	0	0	2
Norway	***6***	17	13	59	1	5	0	1	4
	12	22	8	43	1	18	1	5	3
	24	16	6	28	4	28	2	11	5
	36	13	5	23	5	26	10	11	6
	60	13	4	19	5	24	18	9	5
	1	2	14	84	0	0	0	0	0
	3	7	13	77	0	0	0	1	1
Brazil	***6***	16	9	58	1	2	0	7	6
	12	22	8	40	1	3	1	12	12
	24	20	6	34	1	3	1	11	25
	36	18	5	30	2	3	1	9	32
	60	19	5	24	2	3	1	8	39
	1	3	11	86	0	0	0	0	0
	3	5	14	76	0	2	1	1	0
Chile	***6***	7	13	65	1	5	2	3	2
	12	8	11	47	3	12	2	3	14
	24	5	8	42	3	17	4	2	18
	36	5	8	42	5	17	4	3	16
	60	9	7	38	7	17	4	4	14
	1	2	9	89	0	0	0	0	0
	3	10	19	70	0	0	0	1	0
Russia	***6***	24	17	56	0	0	0	1	1
	12	37	12	44	4	0	1	1	1
	24	42	9	33	5	0	1	1	8
	36	43	8	26	5	1	1	3	13
	60	50	5	17	4	1	2	6	14
	1	8	13	80	0	0	0	0	0
	3	15	16	67	0	0	0	1	1
South	***6***	24	11	60	0	0	0	2	2
Africa	***12***	30	7	54	3	1	0	4	1
	24	25	5	45	12	1	1	6	4
	36	21	7	40	16	1	3	6	6
	60	24	6	31	23	2	3	5	6

Notes: *WIP - World Industrial Production Index; BAA - BAA10YR spread; CXPI - country-specific commodity export price; GDP - real GDP; INFL - CPI inflation; SR - short-term interest rate; REX - real exchange rate; SPX - real equity index. The sample period starts in 1995M1 (1996M1 for Brazil) and ends in 2019M1.*

Table 2.5 Real GDP Forecast error variance decompositions

	Period	*WIP*	*BAA*	*CXPI*	*GDP*	*INFL*	*SR*	*REX*	*SPX*	*Global Shocks*
	1	2	0	0	98	0	0	0	0	2
	3	10	2	0	86	0	1	1	1	12
Australia	***6***	14	2	1	80	0	1	1	1	17
	12	18	2	1	76	1	2	1	1	20
	24	23	1	0	67	2	5	1	1	24
	36	24	1	1	62	3	8	1	0	26
	60	26	1	2	58	3	10	1	0	28
	1	6	0	0	94	0	0	0	0	6
	3	11	2	0	84	1	0	1	1	13
Canada	***6***	21	3	8	61	3	1	1	2	32
	12	24	4	6	49	9	3	2	4	34
	24	15	4	4	53	10	7	4	3	23
	36	12	3	3	51	9	13	4	3	19
	60	10	3	3	48	8	17	9	3	16
	1	1	0	0	99	0	0	0	0	1
	3	2	0	0	96	0	0	2	0	2
New	***6***	3	4	0	87	1	4	1	0	7
Zealand	***12***	3	8	1	80	2	6	1	1	11
	24	5	11	0	71	1	5	3	3	16
	36	12	11	1	57	1	5	6	8	23
	60	29	10	1	30	3	3	5	17	41
	1	1	0	1	98	0	0	0	0	2
	3	2	1	1	95	0	1	0	0	3
Norway	***6***	5	1	1	84	3	5	1	0	7
	12	11	1	2	75	3	7	1	0	13
	24	12	1	3	68	5	9	1	1	17
	36	11	1	4	68	5	8	1	3	16
	60	10	1	3	66	4	11	1	3	15
	1	8	0	1	91	0	0	0	0	9
	3	17	8	1	71	1	2	0	0	26
Brazil	***6***	33	9	1	40	3	3	3	7	44
	12	41	10	1	15	12	3	5	13	52
	24	39	7	3	7	14	2	4	24	49
	36	35	6	3	6	14	2	3	33	43
	60	31	4	2	5	12	1	2	41	38
	1	0	0	0	99	0	0	0	0	1
	3	4	0	0	92	0	3	0	1	4
Chile	***6***	13	0	1	73	1	7	0	6	13
	12	19	0	3	54	3	8	0	12	22
	24	17	0	10	36	14	7	0	16	27
	36	16	1	14	29	17	7	0	16	31
	60	21	2	15	23	18	6	1	13	38
	1	9	0	0	90	0	0	0	0	10
	3	19	2	4	67	1	2	1	3	26
Russia	***6***	35	3	9	45	2	1	3	2	47
	12	48	4	9	31	2	1	5	1	61
	24	51	3	7	20	1	0	8	9	61
	36	49	2	6	14	1	1	10	18	56
	60	52	1	3	8	2	2	12	20	57
	1	1	0	0	99	0	0	0	0	1
	3	9	1	0	87	0	3	1	0	9
South	***6***	24	0	1	69	0	4	0	0	26
Africa	***12***	35	1	1	55	1	8	0	0	36
	24	26	1	1	53	2	11	1	6	27
	36	19	1	1	55	2	8	3	13	20
	60	17	4	1	50	2	6	3	18	22

Notes: *Please refer to Table 2.4*

Table 2.6 Stock market index forecast error variance decompositions

	Period	WIP	BAA	CXPI	GDP	INFL	SR	REX	SPX	Global Shocks
	1	3	29	7	1	0	0	27	32	39
	3	13	28	3	3	0	0	26	26	44
Australia	***6***	17	27	1	9	1	0	23	21	46
	12	14	25	1	21	3	0	22	13	40
	24	11	26	2	28	3	1	19	11	38
	36	10	24	5	27	3	2	17	11	39
	60	10	23	6	28	3	3	16	11	39
	1	1	29	8	0	0	0	23	39	38
	3	9	24	6	0	1	1	22	36	39
Canada	***6***	18	20	4	3	3	1	21	31	41
	12	16	15	2	7	5	1	31	24	33
	24	15	12	2	9	5	1	37	19	29
	36	15	11	2	8	5	2	35	22	28
	60	14	11	3	10	5	3	32	22	28
	1	1	15	2	1	0	0	42	39	18
	3	3	15	5	1	0	0	46	30	23
New	***6***	3	17	6	7	3	0	46	18	26
Zealand	***12***	2	20	3	15	6	1	42	11	26
	24	6	23	2	19	5	2	35	8	32
	36	11	20	4	19	5	3	31	8	35
	60	15	18	4	17	5	3	27	11	37
	1	1	33	12	0	2	1	11	39	46
	3	10	31	7	1	9	5	8	28	48
Norway	***6***	19	22	5	3	15	9	7	20	47
	12	18	15	4	2	18	19	10	12	38
	24	13	11	7	4	20	21	14	10	30
	36	12	10	7	4	20	20	15	12	29
	60	11	9	5	3	20	27	14	10	25
	1	0	23	4	0	1	5	31	36	27
	3	3	20	3	1	0	2	37	33	27
Brazil	***6***	7	21	2	2	0	1	35	31	31
	12	10	20	3	2	1	1	34	29	34
	24	11	17	5	3	1	0	28	33	34
	36	11	16	5	4	2	0	26	36	32
	60	10	15	5	5	2	0	25	38	31
	1	0	24	7	0	2	3	23	41	32
	3	2	18	7	1	3	2	29	37	28
Chile	***6***	3	14	8	3	6	2	24	40	25
	12	4	10	15	3	11	2	17	39	29
	24	3	7	27	3	14	2	11	33	37
	36	5	6	30	5	14	2	9	29	41
	60	11	5	28	6	16	2	8	24	44
	1	0	14	2	5	4	5	18	53	16
	3	1	15	2	12	2	4	12	52	18
Russia	***6***	2	13	3	20	2	5	5	50	18
	12	2	10	2	28	3	7	3	44	14
	24	2	10	4	31	5	8	3	37	16
	36	3	9	6	27	5	7	3	40	18
	60	17	7	5	21	5	7	3	34	29
	1	1	16	7	0	0	7	27	43	23
	3	7	14	7	0	0	9	26	36	28
South	***6***	16	15	5	2	0	13	22	27	35
Africa	***12***	15	19	3	9	0	15	21	17	37
	24	14	17	3	21	0	10	21	13	34
	36	17	15	4	22	1	9	19	12	37
	60	21	13	8	25	1	7	15	10	42

Notes: *Please refer to Table 2.4*

Table 2.7 Industrial Production Index FEVDs [Robustness - Industrial Production Index]

	Period	*WIP*	*BAA*	*CXPI*	*IPI*	*INFL*	*SR*	*REX*	*SPX*	*Global Shocks*
	1	0	0	1	98	0	0	0	0	2
	3	0	0	1	98	0	0	0	0	1
Australia	***6***	0	1	1	96	2	0	1	0	2
	12	0	1	1	89	4	3	1	1	2
	24	5	1	4	66	5	16	1	2	10
	36	6	2	5	63	5	15	1	4	13
	60	8	2	4	62	6	13	1	4	14
	1	3	1	1	96	0	0	0	0	4
	3	6	0	0	86	0	0	3	3	7
Canada	***6***	17	1	5	64	1	3	2	8	23
	12	23	2	3	47	4	10	3	8	28
	24	15	2	2	46	3	21	5	6	19
	36	14	2	2	39	2	28	7	6	17
	60	19	1	2	31	3	24	16	5	22
	1	0	0	0	100	0	0	0	0	0
	3	0	0	0	99	0	0	0	1	0
New	***6***	0	0	0	98	0	0	1	1	0
Zealand	***12***	0	3	1	92	1	1	1	1	4
	24	0	5	6	74	7	5	1	1	11
	36	1	6	7	66	10	6	3	1	14
	60	6	5	6	55	9	7	8	3	18
	1	0	1	0	98	0	0	0	0	2
	3	0	1	1	96	1	0	0	1	2
Norway	***6***	0	2	2	92	2	1	1	1	4
	12	1	3	2	89	2	1	1	1	6
	24	3	6	3	84	2	1	1	1	12
	36	3	7	3	81	2	1	2	1	13
	60	8	7	3	71	7	1	4	1	17
	1	12	0	0	88	0	0	0	0	12
	3	19	14	0	63	0	2	0	1	33
Brazil	***6***	24	18	2	37	0	4	3	11	44
	12	25	14	4	21	1	6	3	25	43
	24	19	11	6	18	3	6	3	35	35
	36	15	8	7	16	8	7	2	37	30
	60	11	6	6	12	17	6	5	36	24
	1	0	0	0	99	0	0	0	0	1
	3	2	2	1	92	1	2	1	0	5
Chile	***6***	10	6	1	73	3	6	1	1	16
	12	13	6	2	61	7	6	1	3	21
	24	10	5	5	45	18	8	3	6	20
	36	9	4	6	38	20	9	8	5	19
	60	12	5	5	31	20	9	14	4	22
	1	9	1	0	90	0	0	0	0	10
	3	16	6	2	65	6	1	1	4	23
Russia	***6***	24	8	6	47	7	0	3	4	38
	12	35	11	8	36	5	0	3	2	53
	24	41	11	10	26	3	1	2	6	62
	36	39	10	10	25	3	2	2	9	59
	60	37	10	10	26	3	3	2	9	56
	1	2	0	0	98	0	0	0	0	2
	3	11	3	0	80	0	2	3	0	15
South	***6***	25	5	3	61	1	2	3	1	33
Africa	***12***	37	4	2	41	1	11	2	1	43
	24	35	4	6	25	1	23	3	3	44
	36	33	3	6	22	1	22	5	7	42
	60	30	5	6	21	1	22	5	10	41

Notes: *IPI - domestic industrial production index. The sample period runs from 1995M1 to 2019M1. For New Zealand, we use the employment rate as an alternative to the real GDP. See Table 2.4 for additional notes.*

Table 2.8 Stock Market FEVD [Robustness - Industrial Production Index]

	Period	*WIP*	*BAA*	*CXPI*	*IPI*	*INFL*	*SR*	*REX*	*SPX*	*Global Shocks*
	1	3	28	7	0	0	0	30	32	37
	3	10	25	4	0	0	1	33	28	38
Australia	***6***	17	22	2	3	1	2	32	22	41
	12	16	15	1	26	2	2	25	13	33
	24	12	12	1	47	3	3	15	8	25
	36	12	10	3	45	4	7	13	7	25
	60	12	9	3	45	4	8	12	7	25
	1	1	28	6	0	0	1	24	40	35
	3	10	21	4	0	1	1	24	39	35
Canada	***6***	20	15	3	0	3	0	24	35	38
	12	23	10	1	0	4	1	33	28	34
	24	27	8	2	0	3	1	36	22	37
	36	27	8	2	0	3	2	36	22	37
	60	26	9	4	1	3	3	34	22	38
	1	1	15	1	0	1	0	41	42	17
	3	2	14	3	3	1	0	43	34	19
New	***6***	3	15	3	5	5	1	46	22	21
Zealand	***12***	2	16	3	11	9	4	43	12	22
	24	8	15	4	20	7	4	33	8	27
	36	12	13	4	25	6	4	29	7	29
	60	13	13	4	27	6	4	26	6	30
	1	1	34	13	0	3	1	11	37	48
	3	9	31	8	1	10	4	10	26	49
Norway	***6***	22	21	5	0	18	7	9	18	49
	12	27	14	3	0	22	15	8	10	44
	24	27	10	4	0	25	20	8	7	40
	36	25	10	4	0	26	18	9	8	38
	60	25	8	3	0	28	20	9	6	37
	1	0	24	4	0	0	6	30	36	28
	3	2	21	5	0	0	3	34	36	28
Brazil	***6***	4	20	4	1	0	3	31	37	29
	12	4	17	5	1	0	3	30	39	27
	24	3	16	6	1	0	3	26	44	26
	36	3	15	7	1	0	4	24	47	25
	60	4	14	7	1	1	4	22	48	24
	1	1	25	6	0	1	5	22	40	32
	3	3	21	7	1	3	3	28	34	31
Chile	***6***	5	17	7	3	5	3	25	36	29
	12	4	13	12	4	10	2	18	35	30
	24	3	9	23	3	14	3	12	32	35
	36	5	7	27	3	13	5	10	30	39
	60	10	6	26	2	17	4	10	24	43
	1	0	11	5	2	5	9	16	52	16
	3	2	11	7	5	3	14	9	49	20
Russia	***6***	6	10	6	11	1	22	4	41	21
	12	10	7	6	18	1	22	3	33	23
	24	16	5	9	22	2	17	2	27	31
	36	17	5	12	19	3	16	2	27	34
	60	21	4	11	20	3	15	2	24	36
	1	1	13	7	1	0	6	28	44	21
	3	12	11	5	0	0	8	26	38	28
South	***6***	26	10	3	0	0	11	22	28	39
Africa	***12***	33	9	2	0	0	14	24	17	44
	24	33	8	3	2	1	13	29	12	44
	36	30	8	5	3	1	12	30	11	44
	60	30	11	9	3	1	10	27	10	50

Notes: *IPI - domestic industrial production index. The sample period runs from 1995M1 to 2019M1. For New Zealand, we use the employment rate as an alternative to the real GDP. See Table 2.4 for additional notes.*

Table 2.9 Real GDP FEVDs [Robustness - VIX]

	Period	*WIP*	*BAA*	*CXPI*	*GDP*	*INFL*	*SR*	*REX*	*SPX*	*Global Shocks*
	1	1	0	0	99	0	0	0	0	1
	3	9	1	0	87	0	0	1	2	10
Australia	***6***	13	1	1	82	0	1	1	1	15
	12	16	1	1	77	1	1	1	2	18
	24	21	1	0	66	5	3	1	2	22
	36	24	1	0	60	6	4	2	4	25
	60	25	1	1	56	6	4	1	5	27
	1	8	0	0	92	0	0	0	0	8
	3	15	1	0	82	0	0	1	2	15
Canada	***6***	28	1	4	61	1	1	1	4	32
	12	35	1	2	46	4	3	1	7	39
	24	26	1	4	48	6	7	3	5	31
	36	22	1	4	46	5	14	3	5	27
	60	19	1	3	46	5	17	3	6	23
	1	0	0	0	100	0	0	0	0	0
	3	1	0	0	96	0	0	2	0	1
New	***6***	2	1	0	91	0	4	2	0	3
Zealand	***12***	1	7	1	79	3	7	2	0	9
	24	5	18	3	58	3	5	7	0	26
	36	9	20	3	46	3	5	11	2	33
	60	20	15	2	28	4	6	11	12	38
	1	1	0	1	99	0	0	0	0	1
	3	1	1	1	95	0	2	0	0	3
Norway	***6***	4	2	2	85	2	5	0	0	7
	12	13	3	1	73	2	8	0	0	16
	24	17	3	1	65	2	10	0	1	22
	36	17	3	1	64	2	9	0	3	21
	60	17	3	1	62	2	11	0	3	21
	1	7	0	0	93	0	0	0	0	7
	3	14	2	1	79	1	2	0	1	17
Brazil	***6***	25	7	5	47	2	4	0	10	37
	12	31	11	6	19	10	3	1	19	47
	24	25	10	9	9	15	2	1	29	44
	36	20	8	10	7	14	3	1	38	37
	60	16	6	8	6	12	3	1	47	30
	1	0	0	0	100	0	0	0	0	0
	3	3	0	0	93	0	3	0	0	3
Chile	***6***	11	2	1	77	1	6	0	3	13
	12	16	4	1	59	2	8	1	9	20
	24	10	4	4	40	13	12	0	16	18
	36	8	3	6	32	17	16	0	17	18
	60	7	3	9	29	18	18	0	15	19
	1	8	1	0	92	0	0	0	0	8
	3	16	4	5	67	1	3	1	4	24
Russia	***6***	32	3	10	46	1	2	3	4	45
	12	47	3	11	31	1	1	5	2	60
	24	55	1	8	22	1	1	6	6	64
	36	53	1	6	15	1	1	7	16	60
	60	53	1	3	7	3	2	8	23	57
	1	1	0	0	98	0	0	0	0	2
	3	7	0	1	89	0	2	1	0	8
South	***6***	16	2	3	74	0	4	1	0	21
Africa	***12***	22	2	4	64	1	6	0	0	28
	24	17	1	2	64	3	6	1	6	20
	36	11	1	1	63	3	4	2	15	13
	60	8	4	1	59	3	3	2	20	13

Notes: *Please refer to Table 2.4*

Table 2.10 Stock Market FEVDs [Robustness - VIX]

	Period	*WIP*	*BAA*	*CXPI*	*GDP*	*INFL*	*SR*	*REX*	*SPX*	*Global Shocks*
	1	3	42	9	1	0	0	19	27	53
	3	14	41	4	2	1	0	16	22	58
Australia	***6***	19	30	3	7	4	0	14	23	52
	12	17	28	2	15	10	0	13	16	46
	24	13	29	2	19	12	0	10	15	44
	36	13	26	4	20	11	2	9	16	43
	60	13	24	6	22	10	2	8	15	42
	1	1	43	7	0	0	0	21	28	51
	3	12	36	4	0	0	0	21	27	52
Canada	***6***	21	22	2	2	1	0	22	29	45
	12	20	13	1	5	2	1	30	27	34
	24	18	10	1	6	3	1	35	24	30
	36	16	9	1	5	4	4	33	26	27
	60	15	9	3	6	4	6	33	24	27
	1	1	23	1	1	0	1	35	39	24
	3	3	31	3	1	0	1	35	27	37
New	***6***	5	24	5	4	3	1	38	21	34
Zealand	***12***	3	25	3	9	7	6	35	13	31
	24	8	33	2	11	7	5	26	8	43
	36	11	34	2	10	6	6	23	7	47
	60	13	35	2	11	5	6	21	7	50
	1	1	36	13	0	2	0	11	37	50
	3	10	35	8	2	8	4	8	26	53
Norway	***6***	22	24	5	3	13	8	7	19	51
	12	23	17	4	2	15	19	9	11	43
	24	16	13	5	3	18	22	13	10	33
	36	13	10	5	4	19	19	18	12	28
	60	10	8	4	4	20	25	19	11	22
	1	0	27	6	0	0	5	28	34	33
	3	5	22	5	0	0	2	31	35	32
Brazil	***6***	11	18	6	1	1	1	27	36	35
	12	14	18	7	1	3	1	24	32	39
	24	15	16	10	2	5	0	18	35	40
	36	14	14	10	3	5	0	16	38	38
	60	13	14	9	4	5	0	15	39	36
	1	1	25	7	0	1	3	22	41	33
	3	2	20	9	1	2	2	28	35	31
Chile	***6***	4	14	10	2	5	2	24	39	28
	12	3	9	17	2	11	3	17	38	29
	24	2	6	25	2	16	6	11	32	33
	36	2	5	28	6	15	7	10	28	34
	60	2	4	28	9	16	7	8	25	34
	1	0	23	2	2	3	5	14	51	25
	3	1	24	2	8	1	5	8	51	27
Russia	***6***	2	16	3	14	2	8	3	52	20
	12	1	11	2	20	5	9	2	49	14
	24	2	10	2	24	9	11	2	40	14
	36	3	10	4	22	9	10	2	41	16
	60	19	8	4	15	8	8	2	35	32
	1	1	31	7	0	0	6	21	34	39
	3	10	22	8	0	0	8	19	32	41
South	***6***	18	22	6	1	0	10	17	25	47
Africa	***12***	16	27	5	5	1	10	20	18	47
	24	14	24	3	11	1	8	22	16	42
	36	15	20	5	14	1	8	21	16	40
	60	13	17	8	22	2	6	17	16	37

Notes: *Please refer to Table 2.4*

Table 2.11 Real GDP FEVDs [Robustness: 2003-2019 period]

	Period	*WIP*	*BAA*	*CXPI*	*GDP*	*INFL*	*SR*	*REX*	*SPX*	*Global Shocks*
	1	3	0	0	97	0	0	0	0	3
	3	6	0	1	90	1	0	1	1	6
Australia	***6***	12	2	1	76	3	0	4	1	15
	12	20	9	3	51	9	3	3	3	31
	24	21	7	5	37	7	10	5	7	34
	36	21	6	10	31	8	13	4	7	37
	60	20	6	13	29	8	13	4	7	39
	1	5	0	0	94	0	0	0	0	6
	3	7	6	0	81	0	0	2	3	14
Canada	***6***	16	22	10	45	1	0	1	5	48
	12	29	33	7	19	5	2	3	4	68
	24	23	35	4	10	6	5	6	10	62
	36	21	24	3	7	5	6	14	20	48
	60	21	17	3	6	9	6	18	20	41
	1	0	0	1	99	0	0	0	0	1
	3	0	3	2	92	0	0	3	0	5
New	***6***	0	24	2	68	1	2	2	1	26
Zealand	***12***	14	26	3	40	1	4	7	6	43
	24	36	21	3	16	2	2	12	8	60
	36	44	16	4	10	1	2	12	11	63
	60	48	12	3	6	1	2	14	16	62
	1	0	0	0	100	0	0	0	0	0
	3	0	1	0	94	2	1	0	2	2
Norway	***6***	0	3	2	82	5	2	1	6	5
	12	1	9	2	69	7	2	3	8	12
	24	2	12	3	62	6	5	3	7	17
	36	8	11	3	55	7	5	5	7	21
	60	9	10	3	49	12	4	5	7	23
	1	8	1	2	90	0	0	0	0	10
	3	15	9	1	71	1	1	2	0	25
Brazil	***6***	24	6	5	43	2	8	8	3	35
	12	23	2	8	23	4	25	12	2	34
	24	15	2	16	13	6	30	16	2	32
	36	13	3	18	10	5	27	21	3	33
	60	11	3	14	7	9	23	30	5	27
	1	0	2	0	98	0	0	0	0	2
	3	1	3	1	92	0	0	0	2	6
Chile	***6***	6	4	2	80	1	0	0	7	12
	12	6	2	3	68	1	0	1	19	11
	24	3	1	5	56	1	1	1	32	9
	36	3	1	5	50	2	2	2	37	8
	60	3	1	7	43	2	2	2	39	11
	1	13	1	1	85	0	0	0	0	15
	3	22	2	4	70	1	0	0	1	28
Russia	***6***	23	2	4	60	1	0	3	6	29
	12	20	2	1	59	3	0	7	7	24
	24	12	3	1	56	12	0	10	5	17
	36	11	3	2	54	15	0	11	5	15
	60	11	4	3	52	14	1	11	5	17
	1	1	1	0	98	0	0	0	0	2
	3	7	1	2	86	1	2	0	2	10
South	***6***	14	1	9	64	1	3	3	7	23
Africa	***12***	14	0	8	50	1	4	8	15	22
	24	7	0	6	50	2	8	9	17	13
	36	6	0	6	53	2	10	9	15	12
	60	6	1	7	50	2	9	13	12	14

Notes: *Please refer to Table 2.4*

Table 2.12 Stock Market FEVDs [Robustness: 2003-2019 period]

	Period	*WIP*	*BAA*	*CXPI*	*GDP*	*INFL*	*SR*	*REX*	*SPX*	*Global Shocks*
	1	2	35	9	0	0	0	26	28	45
	3	12	27	6	3	2	0	26	24	45
Australia	***6***	24	18	8	7	9	2	17	15	49
	12	25	9	11	11	15	9	9	12	45
	24	19	9	13	9	13	19	7	12	41
	36	18	9	16	9	12	19	8	11	42
	60	17	8	15	9	12	20	7	11	41
	1	3	32	13	0	2	2	21	29	47
	3	18	21	13	0	3	3	20	22	53
Canada	***6***	28	18	8	0	4	2	25	15	54
	12	26	11	5	0	7	6	35	9	42
	24	24	10	6	0	9	7	35	8	40
	36	24	10	7	1	9	6	34	9	41
	60	24	10	7	1	9	7	34	9	41
	1	1	28	1	0	0	1	35	35	29
	3	6	23	3	1	0	3	34	30	32
New	***6***	6	22	5	1	2	8	25	31	33
Zealand	***12***	6	17	6	0	3	5	15	47	29
	24	24	12	6	4	2	3	15	33	42
	36	31	10	7	4	2	3	15	27	48
	60	33	9	7	5	2	3	15	26	49
	1	0	31	19	0	2	0	14	34	50
	3	8	28	12	1	12	4	17	20	47
Norway	***6***	18	15	7	1	25	5	17	12	40
	12	17	9	6	3	34	12	12	7	32
	24	14	7	9	4	39	11	10	6	30
	36	15	7	9	4	38	11	10	6	31
	60	15	7	9	5	37	11	10	7	31
	1	1	20	9	0	1	5	33	32	29
	3	6	10	11	0	5	8	33	27	27
Brazil	***6***	12	5	10	0	5	14	34	18	28
	12	12	3	10	1	12	16	36	10	25
	24	8	3	9	1	19	12	40	7	20
	36	8	3	8	1	20	10	44	6	19
	60	7	3	7	3	20	10	43	7	17
	1	0	23	15	0	0	1	22	39	38
	3	1	15	19	2	0	3	21	40	35
Chile	***6***	1	8	15	16	0	3	13	44	24
	12	1	4	18	14	0	1	6	57	22
	24	1	3	30	9	1	1	4	52	34
	36	1	2	33	10	1	2	3	47	36
	60	2	2	34	22	1	4	3	34	37
	1	0	27	18	1	0	3	8	43	45
	3	5	24	14	3	1	3	7	43	43
Russia	***6***	6	18	9	11	1	5	4	46	34
	12	4	10	5	23	9	6	5	36	20
	24	5	9	7	23	18	8	4	27	21
	36	7	8	11	20	15	10	5	24	26
	60	8	8	11	18	14	12	6	23	27
	1	1	19	9	0	0	0	39	31	30
	3	9	17	7	1	1	0	31	34	33
South	***6***	16	15	4	7	2	2	20	34	35
Africa	***12***	13	10	6	18	4	7	14	28	29
	24	13	8	7	25	3	8	12	23	28
	36	13	9	8	26	3	8	12	22	30
	60	13	8	9	24	3	7	15	20	30

Notes: *Please refer to Table 2.4*

Table 2.13 Real GDP FEVDs [Robustness - non-detrended data]

	Period	*WIP*	*BAA*	*CXPI*	*GDP*	*INFL*	*SR*	*REX*	*SPX*	*Global Shocks*
	1	1	0	0	99	0	0	0	0	1
	3	8	1	0	88	0	1	1	1	9
Australia	***6***	10	1	0	84	0	1	1	2	11
	12	12	1	0	81	1	2	1	3	13
	24	17	1	1	71	2	5	0	4	18
	36	19	1	2	62	2	8	0	6	21
	60	19	2	5	51	2	9	0	12	26
	1	5	0	0	95	0	0	0	0	5
	3	10	2	1	84	0	0	1	1	13
Canada	***6***	20	5	9	60	3	1	1	2	33
	12	23	8	6	46	10	2	1	3	38
	24	16	9	6	46	12	7	2	3	30
	36	12	6	6	37	11	18	4	7	24
	60	10	4	9	22	8	30	8	10	23
	1	0	0	0	100	0	0	0	0	0
	3	1	0	0	97	0	0	2	0	1
New	***6***	1	4	0	90	1	3	1	0	5
Zealand	***12***	1	8	0	80	2	7	1	0	10
	24	7	10	2	67	1	9	2	0	20
	36	13	9	3	59	2	11	3	0	25
	60	20	8	5	46	3	13	5	0	34
	1	1	0	1	99	0	0	0	0	1
	3	1	1	1	94	0	2	0	0	3
Norway	***6***	4	1	1	84	2	6	1	0	6
	12	10	2	1	73	3	10	1	1	13
	24	17	1	1	60	3	13	1	4	19
	36	17	2	1	55	3	11	2	9	20
	60	18	7	4	45	2	8	2	13	29
	1	9	0	1	90	0	0	0	0	10
	3	20	10	1	67	0	2	0	0	30
Brazil	***6***	38	11	1	35	3	4	1	6	51
	12	49	11	1	13	11	4	3	8	61
	24	57	9	1	7	12	4	3	8	66
	36	59	7	1	6	12	4	2	9	67
	60	60	6	0	5	13	4	2	11	66
	1	0	0	0	100	0	0	0	0	0
	3	2	0	0	94	0	3	0	0	2
Chile	***6***	8	0	1	79	1	7	0	4	9
	12	11	1	1	64	3	10	0	10	12
	24	7	1	2	50	14	13	0	13	11
	36	7	1	4	42	18	15	0	13	12
	60	11	3	7	30	23	14	0	11	21
	1	9	0	0	90	0	0	0	0	10
	3	20	1	8	64	1	2	1	3	29
Russia	***6***	34	1	15	40	2	1	3	3	51
	12	43	2	20	26	2	0	4	2	65
	24	37	1	24	15	2	0	6	14	63
	36	27	2	25	10	2	0	6	27	54
	60	24	4	26	7	2	0	7	29	54
	1	1	0	0	99	0	0	0	0	1
	3	8	1	0	87	0	4	1	0	9
South	***6***	24	1	2	66	0	6	0	0	27
Africa	***12***	35	2	2	47	1	13	0	0	39
	24	28	1	1	40	2	20	4	4	30
	36	21	2	1	39	1	16	9	12	23
	60	21	6	2	34	2	11	9	16	29

Notes: *Please refer to Table 2.4*

Table 2.14 Stock Market Index FEVDs [Robustness - non-detrended data]

	Period	*WIP*	*BAA*	*CXPI*	*GDP*	*INFL*	*SR*	*REX*	*SPX*	*Global Shocks*
	1	4	29	6	1	0	0	27	33	39
	3	14	27	2	3	0	0	24	29	43
Australia	***6***	18	27	1	6	1	0	20	26	46
	12	15	27	1	12	4	0	20	20	43
	24	13	31	1	16	4	0	18	17	45
	36	12	30	4	15	4	2	17	16	46
	60	11	29	5	16	4	3	17	15	45
	1	1	29	8	0	0	0	23	39	38
	3	8	24	7	0	1	0	23	37	39
Canada	***6***	15	21	5	3	3	0	22	32	40
	12	12	17	3	6	4	2	31	25	31
	24	9	14	4	10	3	3	37	20	26
	36	9	13	6	10	3	3	36	20	28
	60	8	13	10	11	3	3	34	19	30
	1	1	15	1	1	0	0	41	41	17
	3	4	13	5	1	0	1	44	32	22
New	***6***	7	13	6	5	2	1	46	21	26
Zealand	***12***	5	16	4	12	5	1	44	14	25
	24	10	19	3	18	4	1	36	10	32
	36	14	16	3	20	4	1	31	9	34
	60	18	14	3	21	5	1	27	10	35
	1	1	33	12	0	2	1	11	40	46
	3	8	31	8	2	10	5	7	30	47
Norway	***6***	17	23	6	3	15	8	7	22	46
	12	15	18	5	2	19	18	10	14	37
	24	11	13	8	3	21	19	13	12	32
	36	11	12	8	3	20	19	14	13	30
	60	9	9	6	2	20	28	13	11	25
	1	0	24	4	0	1	5	32	34	28
	3	3	21	4	0	0	2	37	33	28
Brazil	***6***	10	21	3	1	1	1	34	30	33
	12	15	21	3	1	3	1	31	25	38
	24	20	19	3	1	5	1	25	26	41
	36	21	18	3	1	5	1	23	28	41
	60	21	17	3	1	6	1	22	29	41
	1	1	21	6	0	2	2	23	44	29
	3	6	16	7	2	3	2	25	39	29
Chile	***6***	8	13	8	4	6	1	19	41	29
	12	6	9	13	6	13	1	12	40	28
	24	4	7	21	5	17	3	8	36	32
	36	5	6	25	7	15	3	7	31	36
	60	7	5	25	13	17	2	6	25	38
	1	0	15	3	5	4	7	14	54	17
	3	2	15	3	16	1	4	8	50	20
Russia	***6***	5	12	3	24	1	5	3	47	20
	12	5	9	3	30	2	4	2	45	18
	24	5	9	10	30	2	3	2	39	23
	36	4	8	19	23	3	3	2	37	32
	60	4	11	26	18	3	5	2	32	41
	1	1	13	7	0	0	7	29	43	22
	3	8	10	6	1	0	10	28	36	25
South	***6***	19	9	4	3	0	15	24	26	32
Africa	***12***	20	9	4	5	0	19	26	17	33
	24	17	9	4	9	0	16	32	12	30
	36	18	10	9	8	0	14	31	10	37
	60	22	12	16	6	0	11	24	9	51

Notes: *Please refer to Table 2.4*

Table 2.15 Real GDP FEVDs [Robustness - Quarterly Data]

	Period	*WIP*	*BAA*	*CXPI*	*GDP*	*INFL*	*SR*	*REX*	*SPX*	*Global Shocks*
	1	10	5	0	85	0	0	0	0	15
	2	12	5	1	80	0	1	0	0	19
Australia	***4***	18	5	2	70	1	4	0	0	25
	8	29	4	1	53	1	12	0	0	34
	12	33	4	1	46	0	16	0	0	38
	20	31	7	1	41	0	17	1	1	40
	1	12	1	1	87	0	0	0	0	13
	2	23	0	3	67	4	2	0	0	26
Canada	***4***	27	2	2	49	12	7	1	1	31
	8	18	2	4	49	12	10	6	1	23
	12	15	1	3	49	11	14	5	2	19
	20	14	1	2	49	9	16	6	2	18
	1	0	0	0	99	0	0	0	0	1
	2	2	2	0	92	0	2	2	0	5
New	***4***	2	5	1	84	0	4	2	1	8
Zealand	***8***	4	8	1	77	2	3	3	2	13
	12	11	9	1	63	2	2	6	6	21
	20	27	14	0	37	1	2	7	13	41
	1	0	0	1	99	0	0	0	0	1
	2	3	0	1	90	2	3	0	1	4
Norway	***4***	10	0	1	79	2	6	0	1	11
	8	17	1	0	71	3	7	1	1	18
	12	15	1	0	71	3	6	2	2	16
	20	14	1	0	67	3	9	3	3	15
	1	24	5	0	71	0	0	0	0	29
	2	36	5	3	45	2	7	0	3	43
Brazil	***4***	39	3	4	22	8	12	0	12	46
	8	35	2	9	11	11	13	0	19	46
	12	33	4	9	8	10	13	1	22	46
	20	35	3	6	5	10	12	3	26	44
	1	4	0	0	96	0	0	0	0	4
	2	12	0	0	79	0	6	0	2	12
Chile	***4***	18	0	0	63	2	8	1	8	19
	8	15	0	3	51	11	6	1	12	19
	12	15	1	9	42	15	5	1	12	25
	20	22	3	13	28	18	4	1	11	38
	1	27	0	3	71	0	0	0	0	29
	2	46	0	2	47	4	1	0	1	48
Russia	***4***	59	1	1	22	13	0	3	1	61
	8	61	3	1	9	15	0	3	8	65
	12	60	4	1	6	14	0	2	12	66
	20	57	6	2	4	14	0	2	14	65
	1	12	0	0	88	0	0	0	0	12
	2	23	0	0	76	0	1	0	0	23
South	***4***	30	0	0	65	2	2	0	0	31
Africa	***8***	21	0	0	68	5	1	0	3	22
	12	15	2	0	68	4	2	0	8	17
	20	15	8	1	58	3	5	0	9	24

Notes: *WIP - World Industrial Production Index; BAA - BAA10YR spread; CXPI - country-specific commodity export price; GDP - real GDP; INFL - CPI inflation; SR - short-term interest rate; REX - real exchange rate; SPX - real equity index. The sample period starts in 1995Q1 (1996Q1 for Brazil) and ends in 2019Q1.*

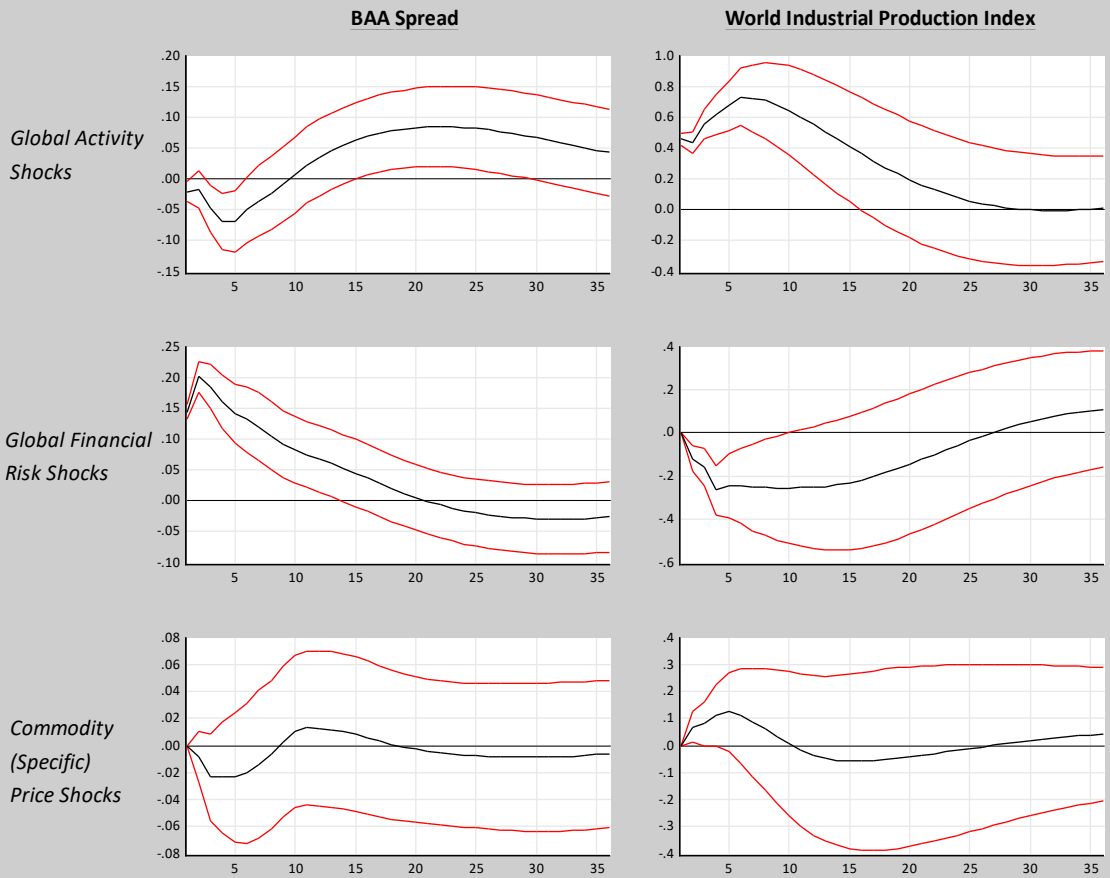
Table 2.16 Stock Market FEVDs [Robustness - Quarterly Data]

	Period	*WIP*	*BAA*	*CXPI*	*GDP*	*INFL*	*SR*	*REX*	*SPX*	*Global Shocks*
	1	19	30	2	1	0	1	23	23	52
	2	30	21	1	2	0	1	27	18	52
Australia	***4***	41	13	1	8	1	1	24	11	55
	8	44	11	1	15	0	2	20	7	56
	12	41	10	3	16	1	2	19	7	55
	20	38	11	7	14	1	4	19	7	55
	1	30	26	5	1	2	0	10	27	60
	2	37	17	2	2	5	0	12	26	56
Canada	***4***	38	12	2	3	5	0	20	19	52
	8	37	9	2	4	5	0	26	15	48
	12	35	9	3	5	6	1	26	17	47
	20	32	9	3	7	6	1	25	16	44
	1	9	23	3	0	0	3	37	25	35
	2	7	22	2	4	1	1	42	22	31
New	***4***	4	24	1	8	1	1	45	16	29
Zealand	***8***	7	24	2	11	2	3	41	11	32
	12	11	19	8	10	3	8	33	9	37
	20	14	16	10	11	3	8	28	10	41
	1	26	37	8	0	5	1	3	19	72
	2	31	23	4	1	10	10	6	15	58
Norway	***4***	32	14	2	1	10	21	9	10	48
	8	26	9	2	3	10	26	17	7	37
	12	21	9	2	4	14	22	21	7	32
	20	19	11	2	4	20	20	18	7	32
	1	19	19	8	0	2	11	19	21	46
	2	24	14	5	1	2	12	17	25	43
Brazil	***4***	27	9	4	1	4	13	15	27	40
	8	27	6	4	2	5	13	15	29	37
	12	27	6	3	2	4	13	15	29	36
	20	28	5	3	2	5	12	15	30	36
	1	7	24	6	1	3	0	33	24	38
	2	8	17	4	6	6	0	29	30	29
Chile	***4***	12	11	9	10	11	0	19	29	32
	8	12	6	25	8	16	0	10	22	44
	12	15	5	30	6	16	0	8	19	50
	20	22	4	28	4	19	0	7	16	53
	1	6	26	3	13	12	5	3	31	35
	2	9	16	1	26	5	9	2	32	26
Russia	***4***	11	12	1	32	4	12	1	28	23
	8	10	10	1	28	12	12	1	26	22
	12	10	10	2	26	14	11	1	28	21
	20	11	11	1	25	14	10	1	27	23
	1	13	22	6	3	5	11	18	23	41
	2	17	19	4	3	6	14	15	23	39
South	***4***	15	24	3	9	7	13	15	16	41
Africa	***8***	11	22	3	23	4	9	14	14	36
	12	10	18	7	28	4	9	12	12	35
	20	14	16	9	33	4	8	9	9	38

Notes: *WIP - World Industrial Production Index; BAA - BAA10YR spread; CXPI - country-specific commodity export price; GDP - real GDP; INFL - CPI inflation; SR - short-term interest rate; REX - real exchange rate; SPX - real equity index. The sample period starts in 1995Q1 (1996Q1 for Brazil) and ends in 2019Q1.*

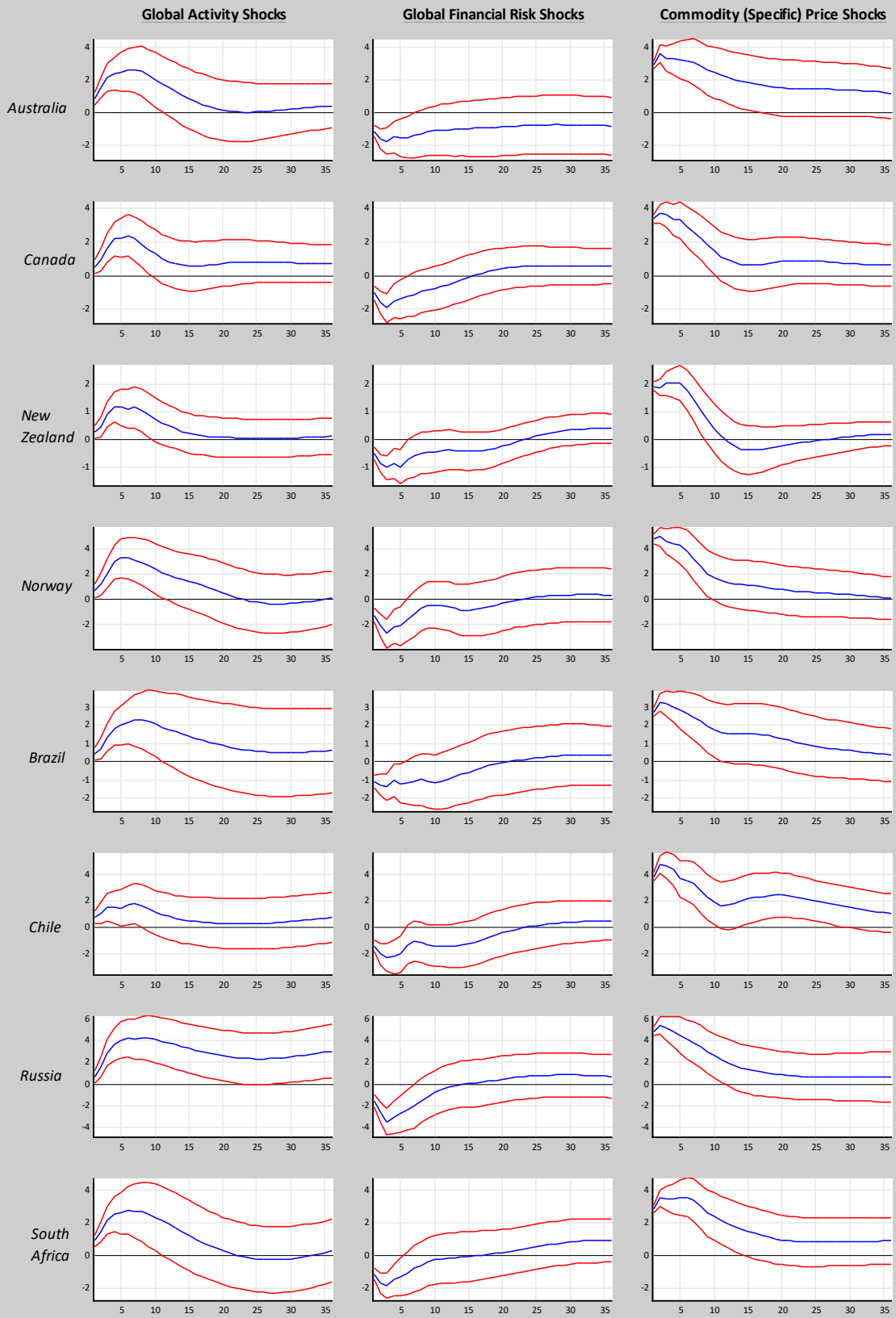
2.8.2 Figures

Figure 2.1 Global variables' impulse responses to global shocks



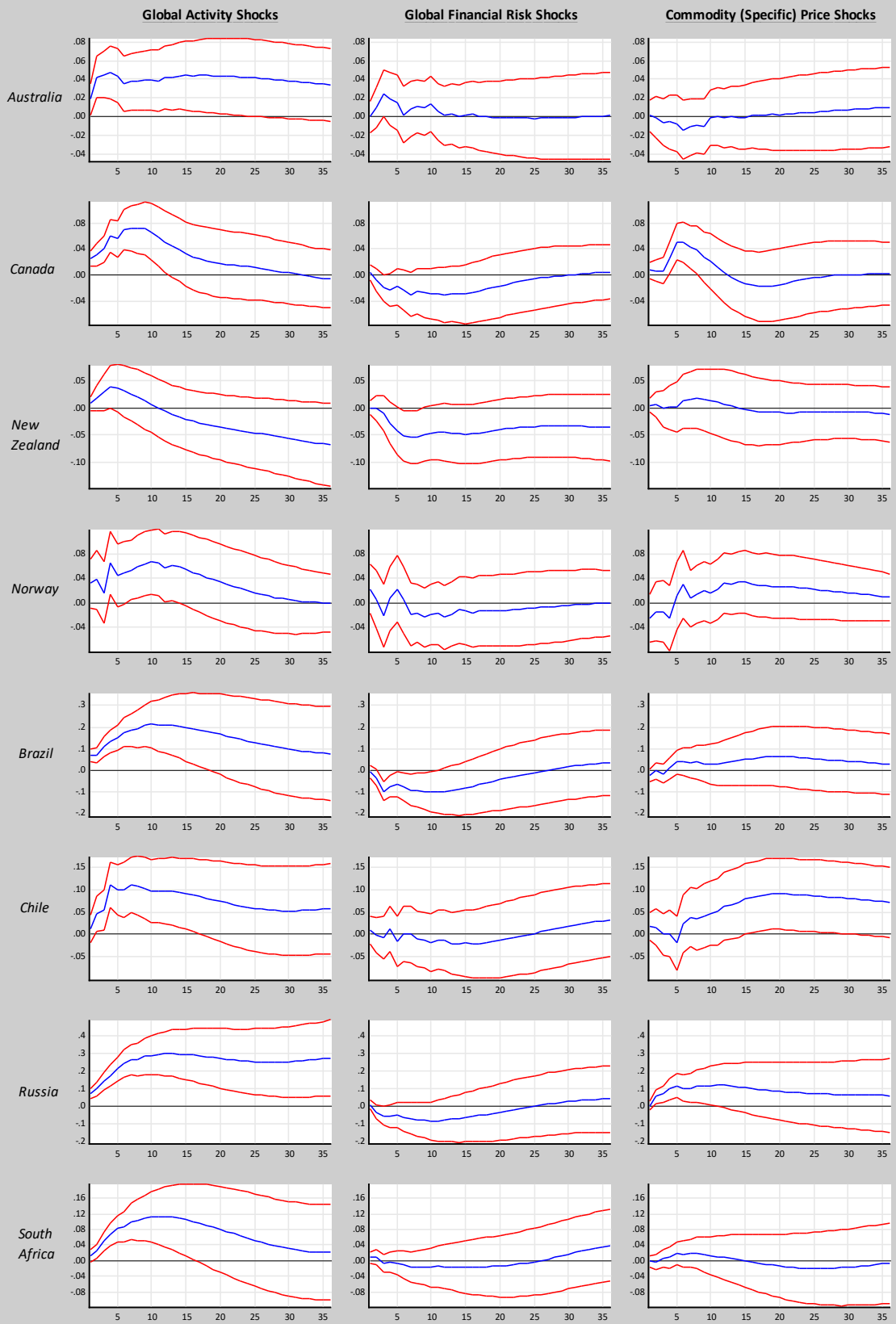
Notes: The figure reports the averaged impulse responses with the 95% confidence intervals. The sample period starts January 1995 (January 1996 for Brazil) and ends December 2019.

Figure 2.2 CXPI responses to one-standard-deviation shocks to the global variables



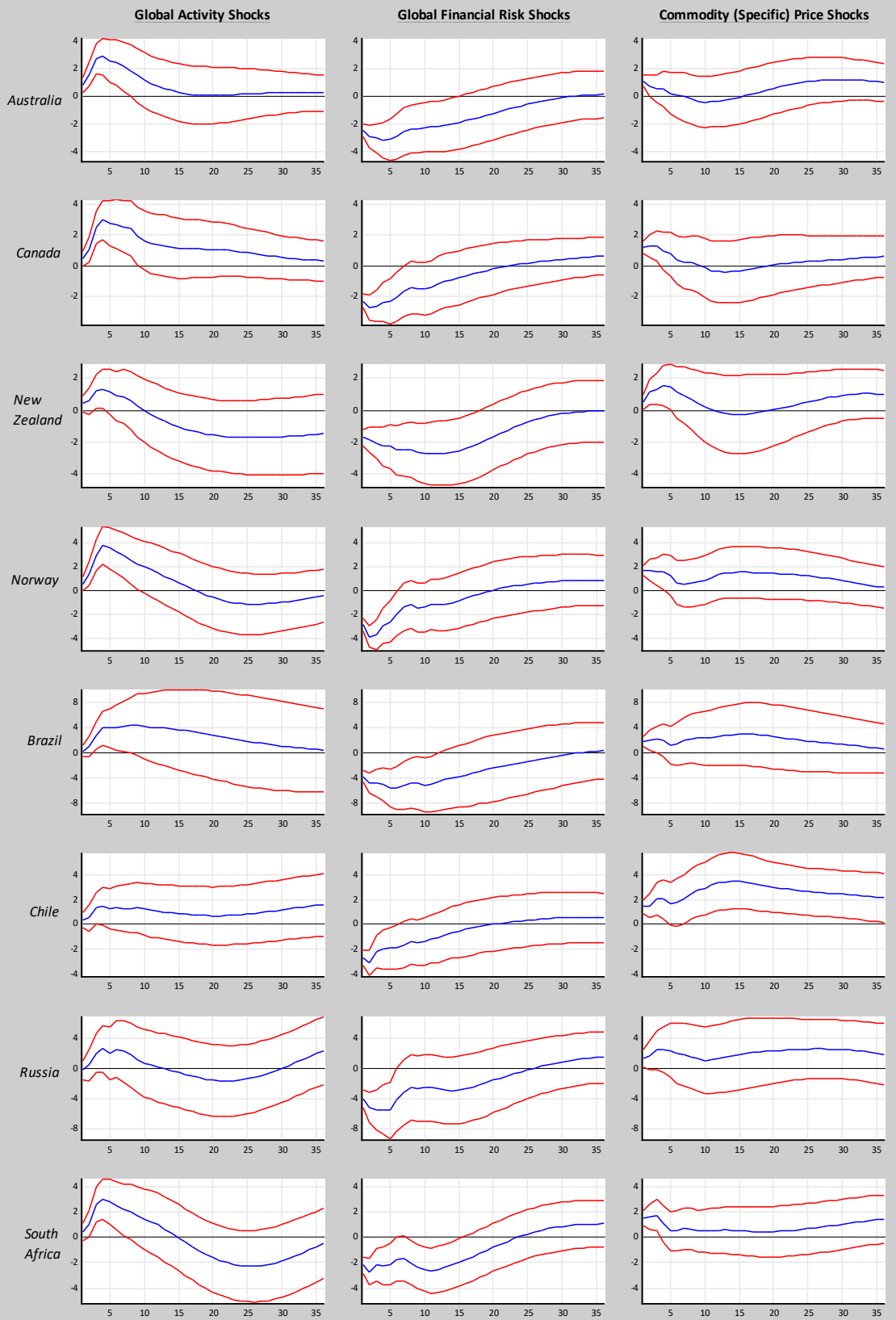
Notes: The figure shows the impulse responses with 95% confidence intervals. CXPI denotes the country-specific commodity export price index. The sample period starts in 1995:1 (1996:1 for Brazil) and ends in 2019:12.

Figure 2.3 Real GDP responses to the global shocks



Notes: The figure shows the impulse responses with 95% confidence intervals. The sample period starts in 1995M1 (1996M1 for Brazil) and ends in 2019M12.

Figure 2.4 Stock market responses to the global shocks



Notes: The figure shows the impulse responses with 95% confidence intervals. The sample period starts in 1995M1 (1996M1 for Brazil) and ends in 2019M12.

Figure 2.5 Averaged percentage contributions of global shocks

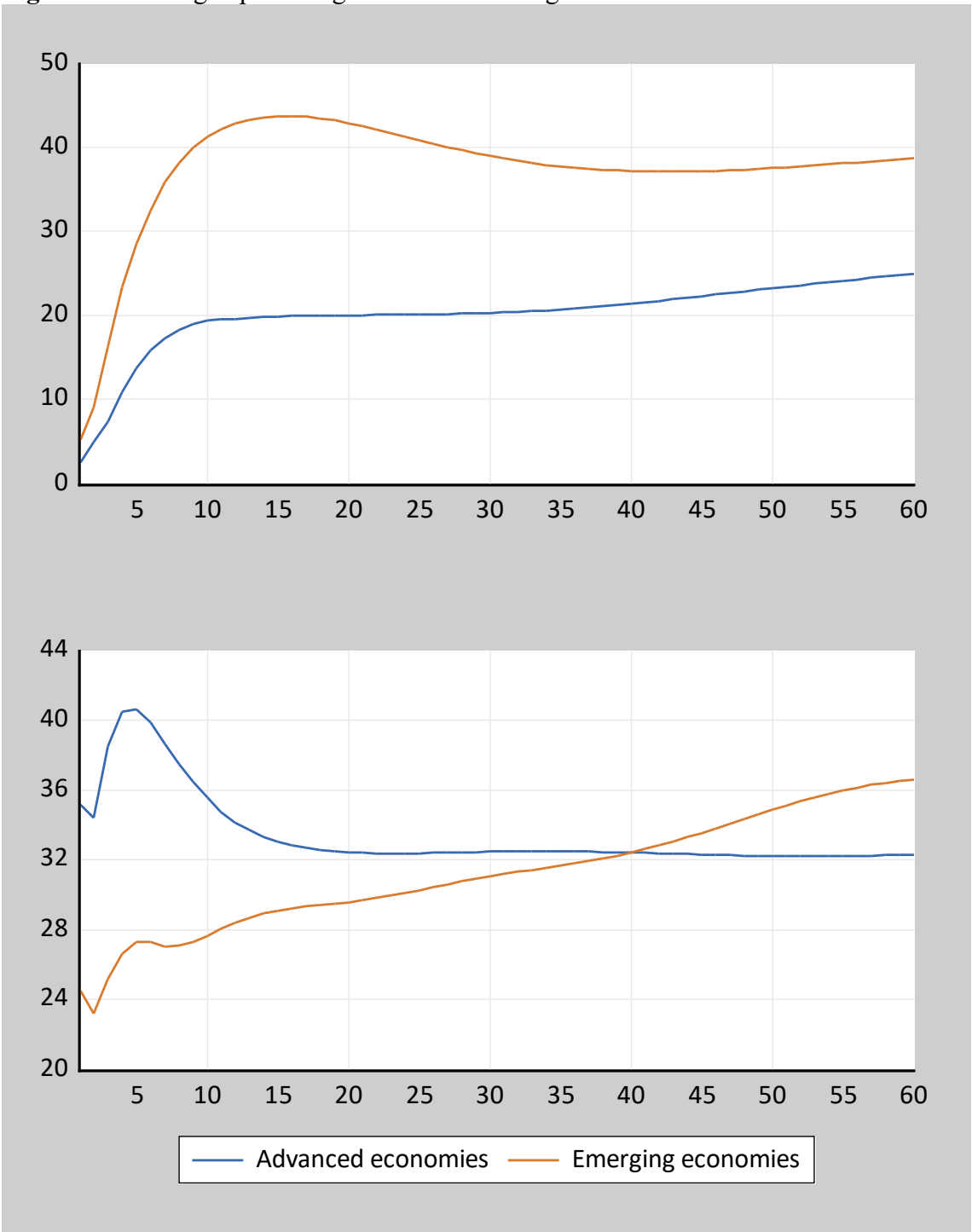
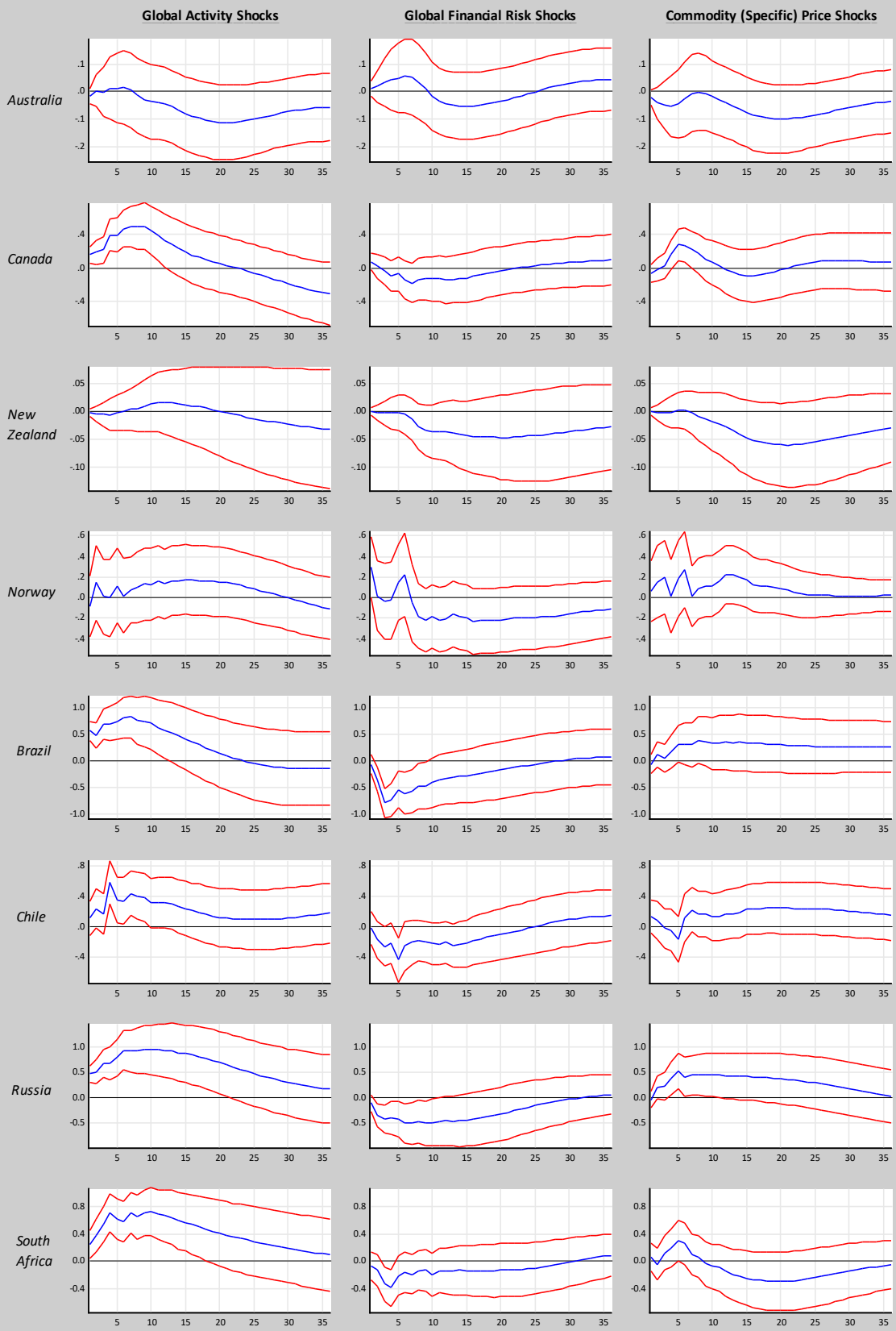
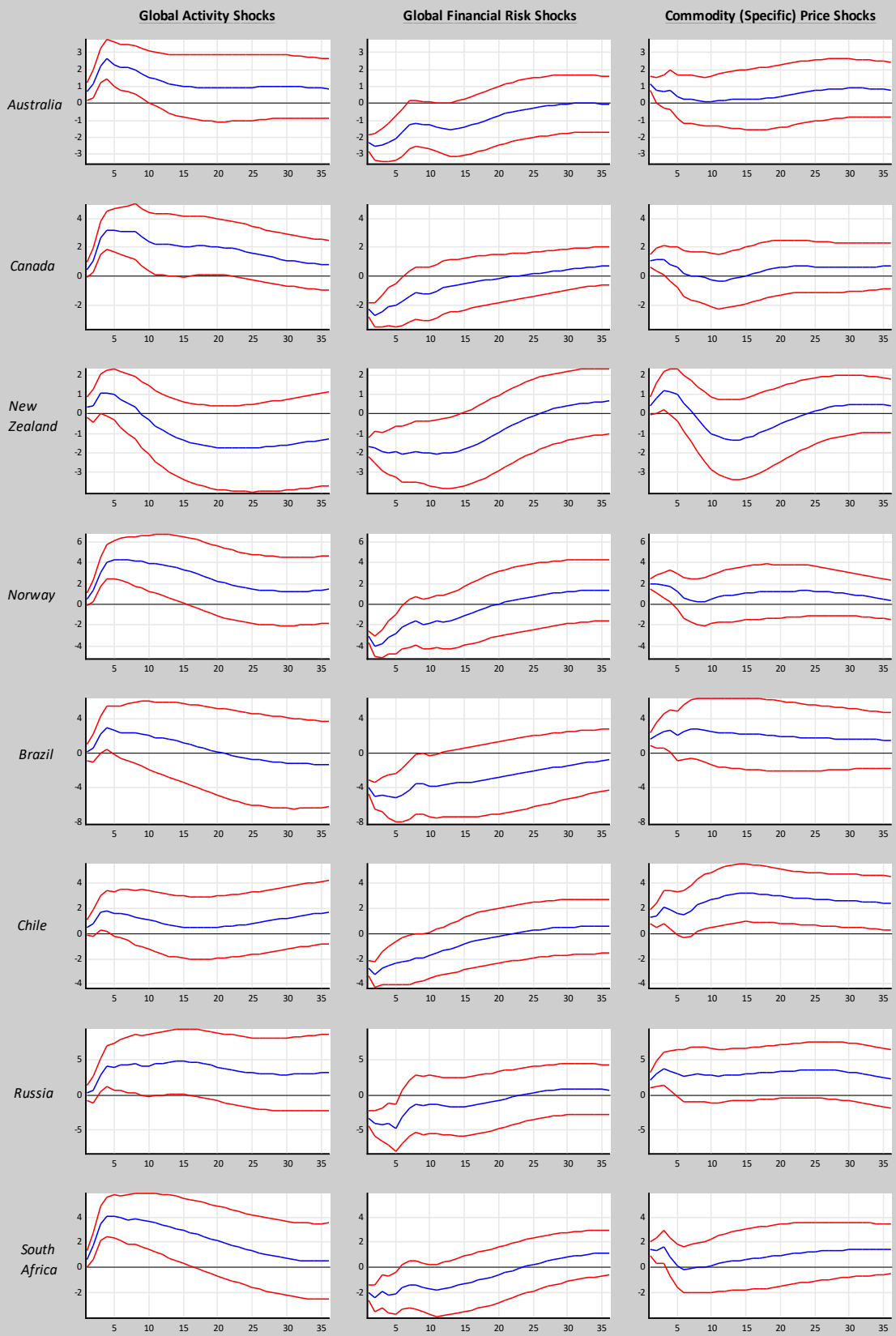


Figure 2.6 Industrial production index responses to the global shocks [Robustness]



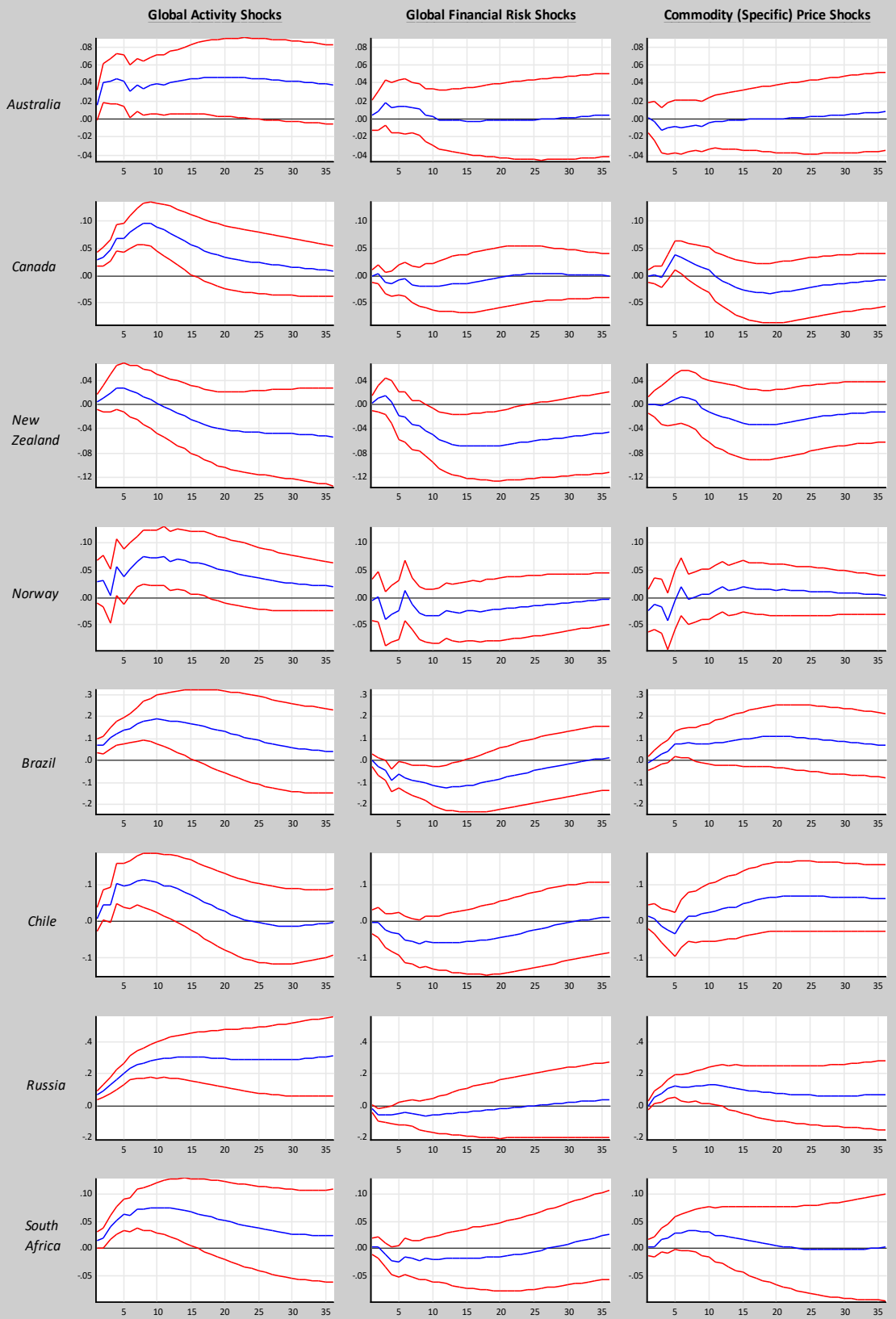
Notes: The figure reports the impulse responses with the 95% confidence intervals. For New Zealand we use the employment rate. Sample period starts 1995M1 and ends 2019M12.

Figure 2.7 Stock market responses to global shocks [Robustness - IPI]



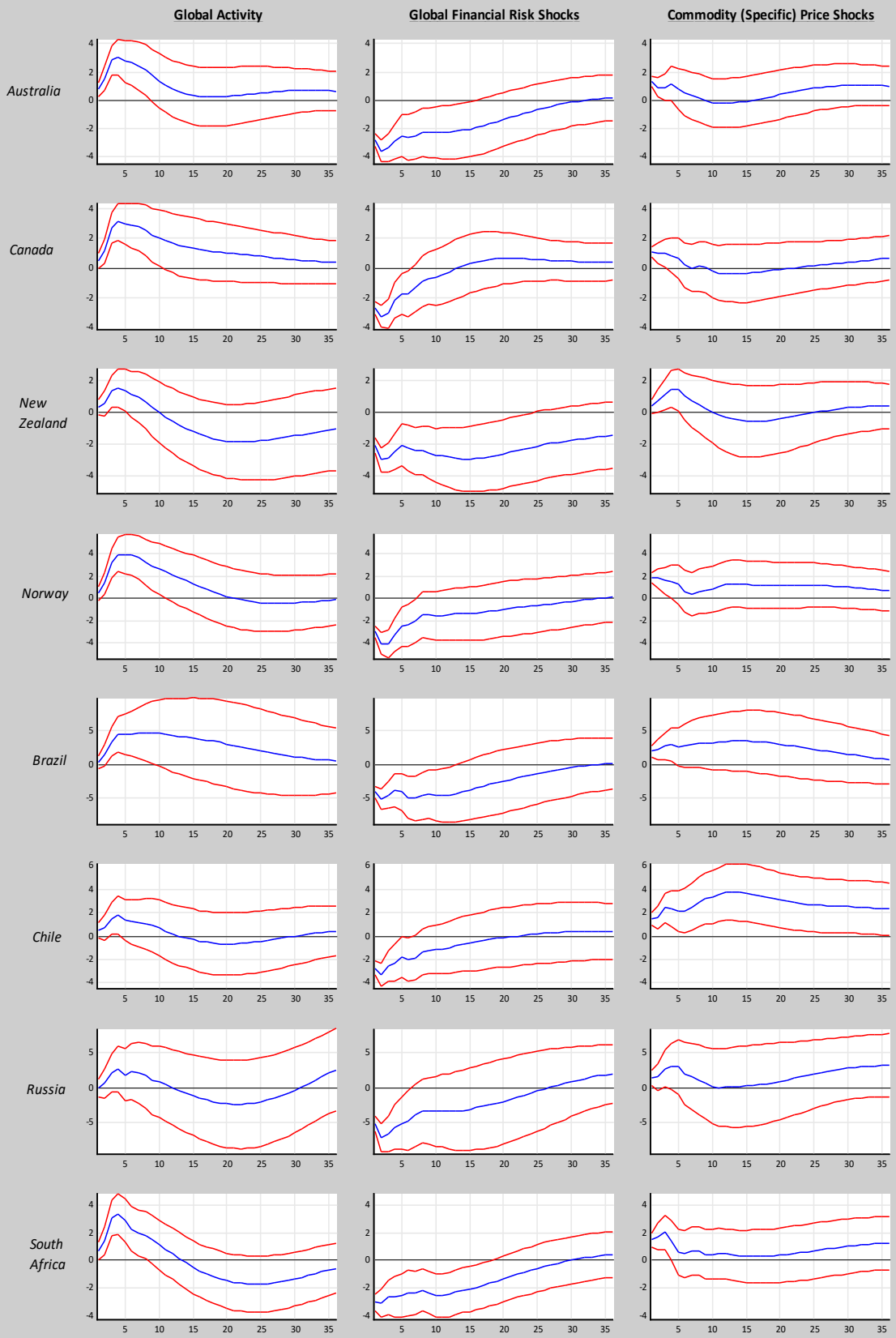
Notes: The figure reports the impulse responses with the 95% confidence intervals. For New Zealand we use the employment rate. Sample period starts 1995M1 and ends 2019M12.

Figure 2.8 Real GDP response to the global shocks [Robustness - VIX]



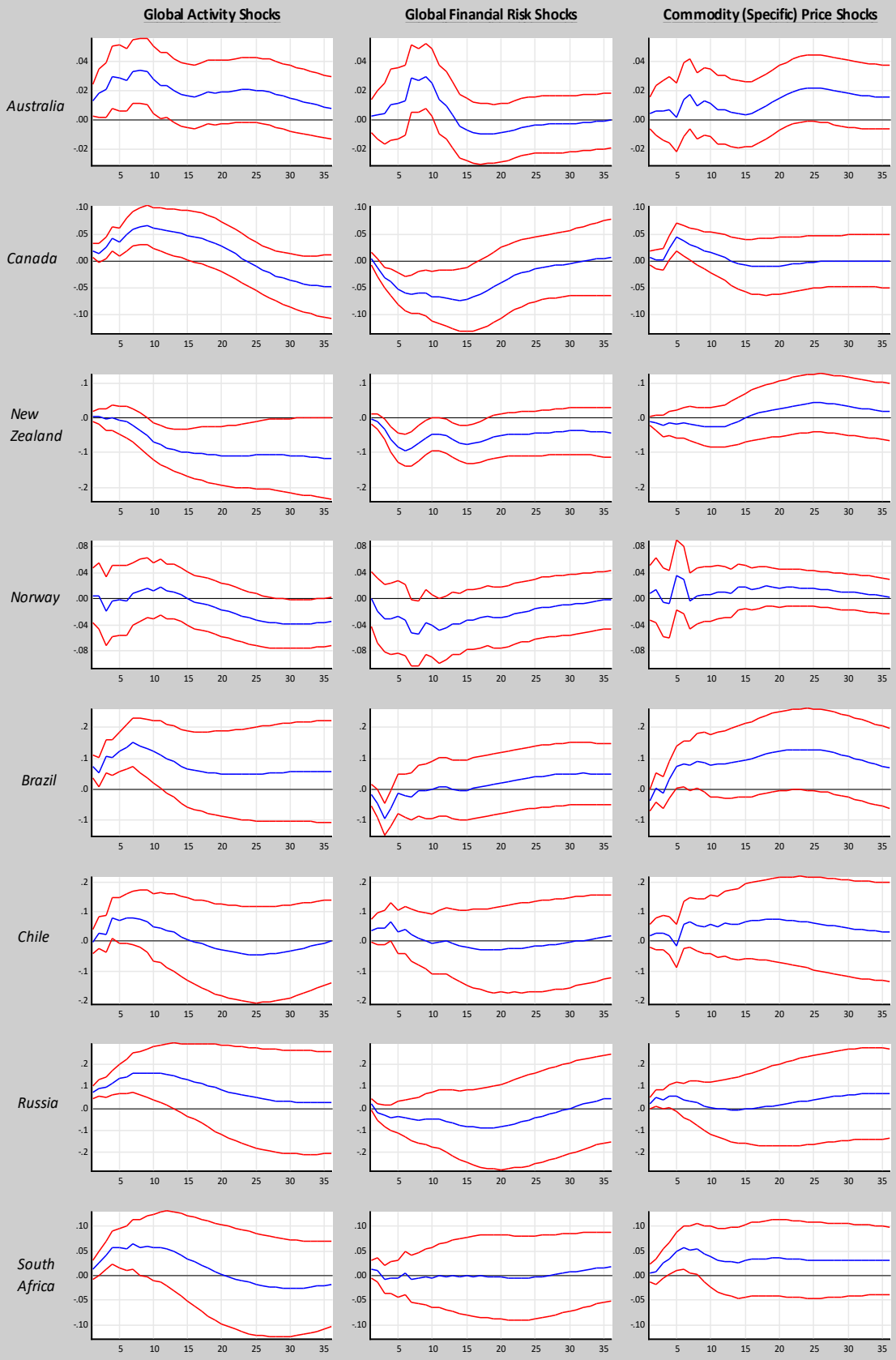
Notes: The figure shows the impulse responses with 95% confidence intervals. The sample period starts in 1995M1 (1996M1 for Brazil) and ends in 2019M12.

Figure 2.9 Stock market response to the global shocks [Robustness - VIX]



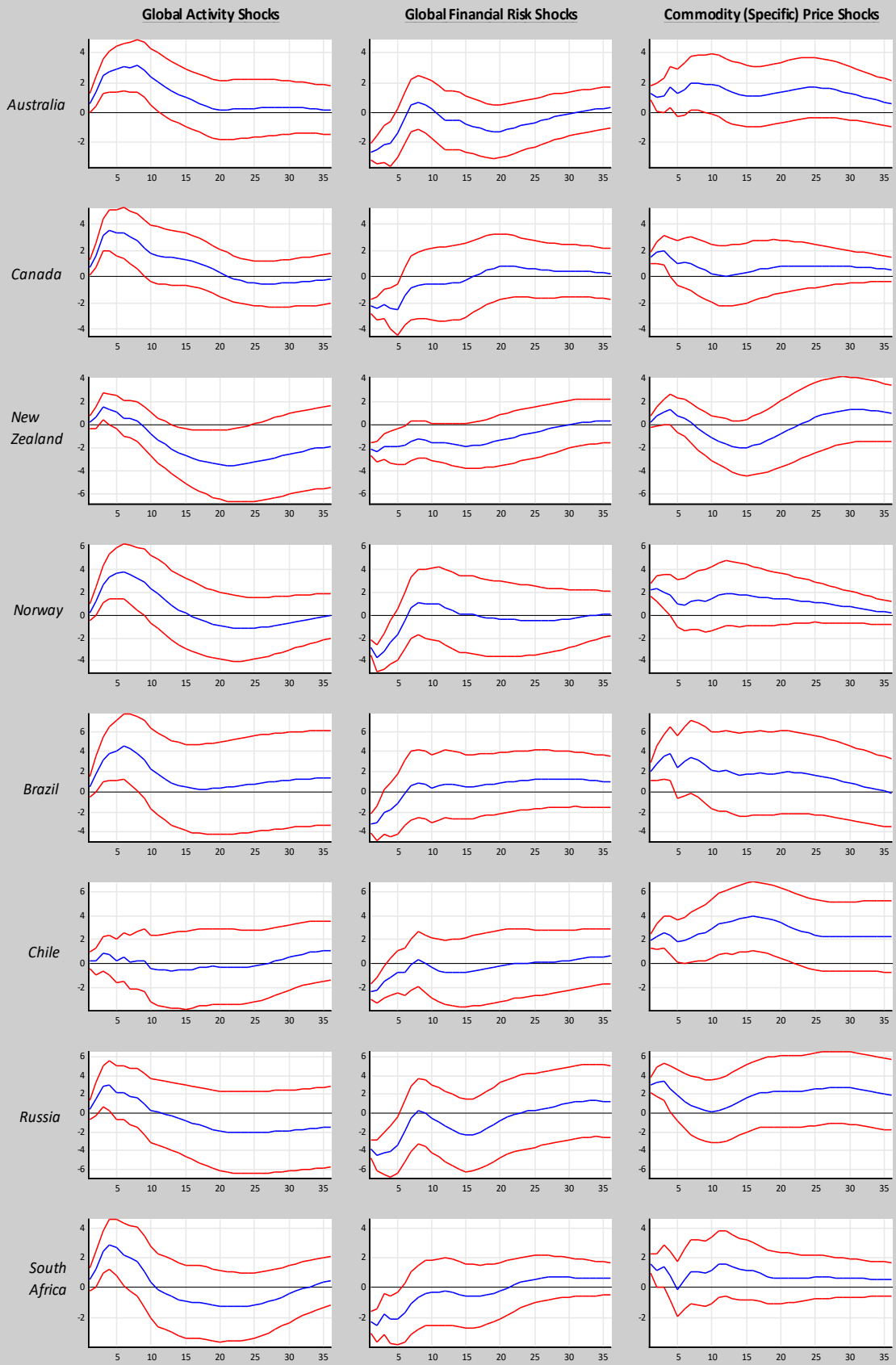
Notes: The figure shows the impulse responses with 95% confidence intervals. The sample period starts in 1995M1 (1996M1 for Brazil) and ends in 2019M12.

Figure 2.10 Real GDP response to global shocks [Robustness: 2003-2019 sample]



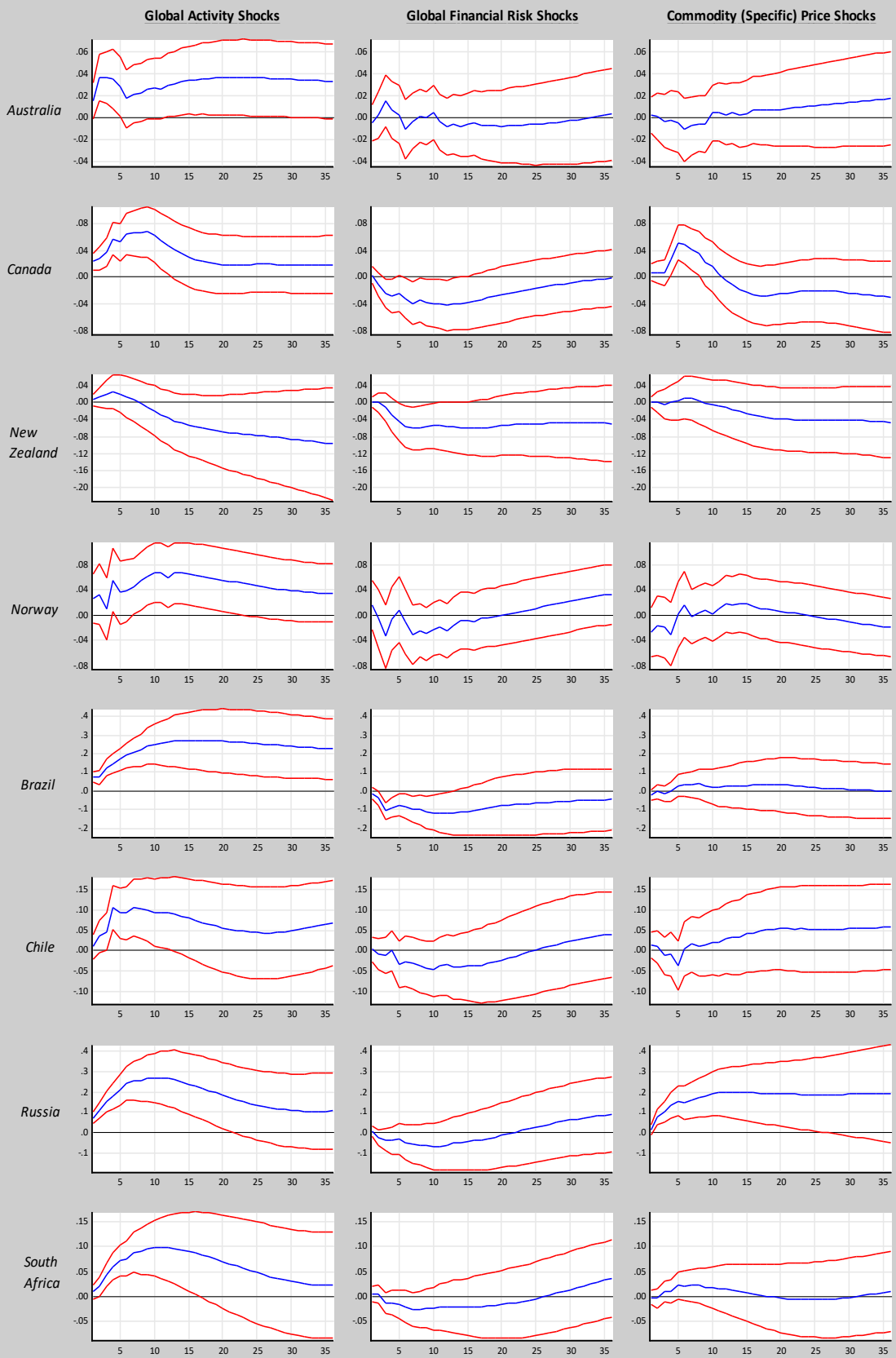
Notes: The figure shows the impulse responses with 95% confidence intervals. The sample period starts from 2003M1 to 2019M12.

Figure 2.11 Stock market responses to global shocks [Robustness: 2003-2019 sample]



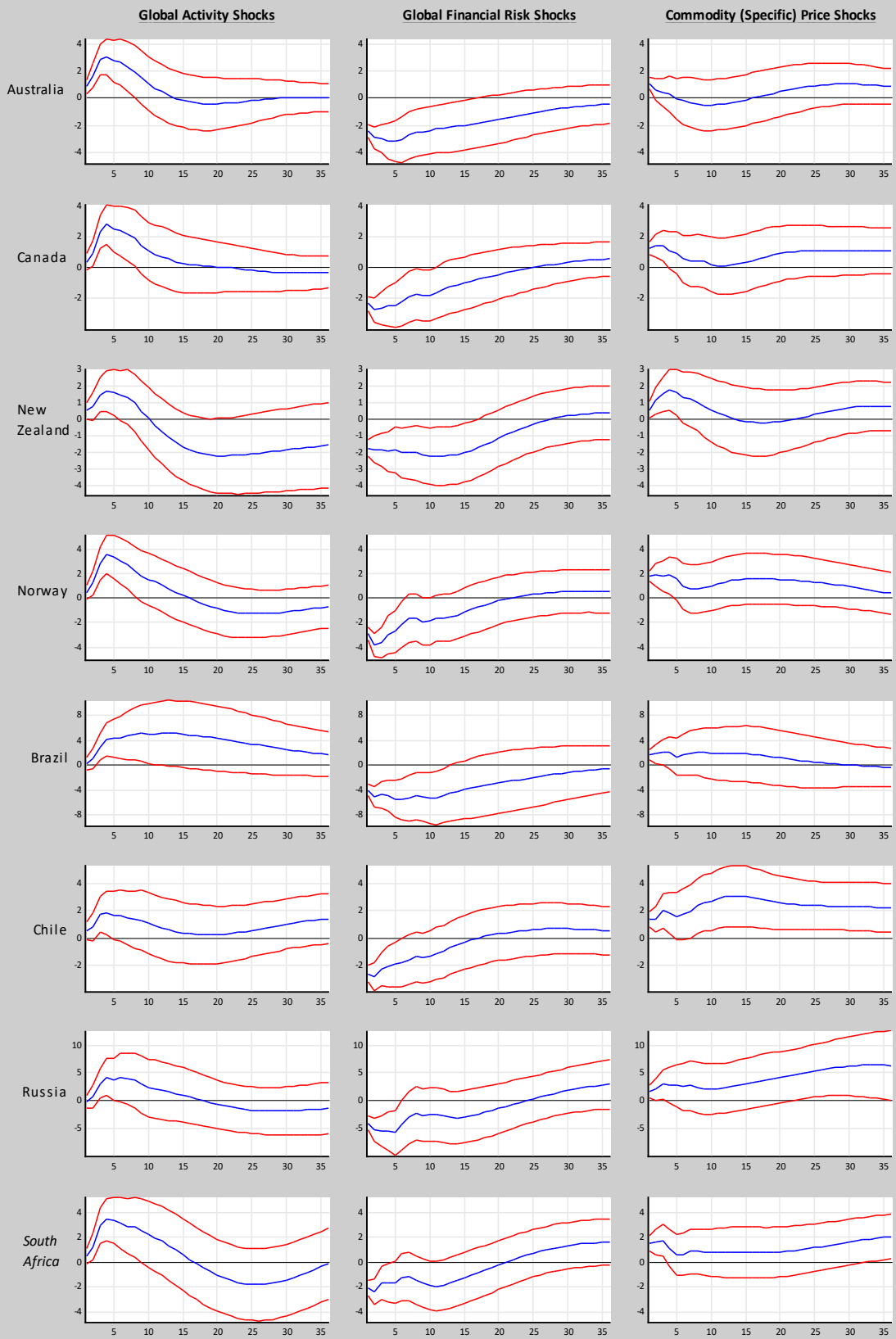
Notes: The figure shows the impulse responses with 95% confidence intervals. The sample period starts from 2003M1 to 2019M12.

Figure 2.12 Real GDP responses to global shocks [Robustness - non-detrended]



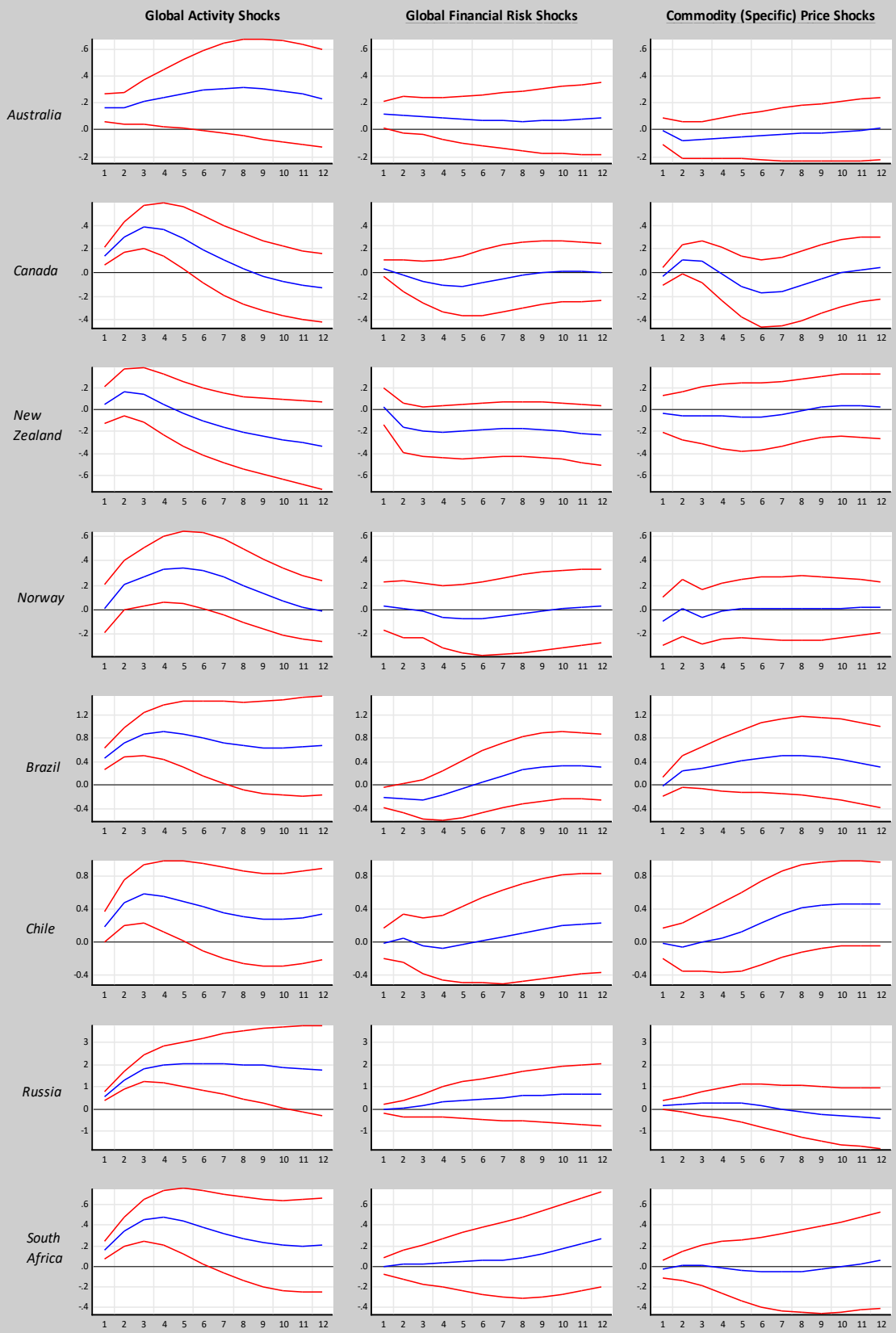
Notes: The figure shows the impulse responses with 95% confidence intervals. The sample period starts in 1995M1 (1996M1 for Brazil) and ends in 2019M12.

Figure 2.13 Stock market responses to global shocks [Robustness - non-detrended]



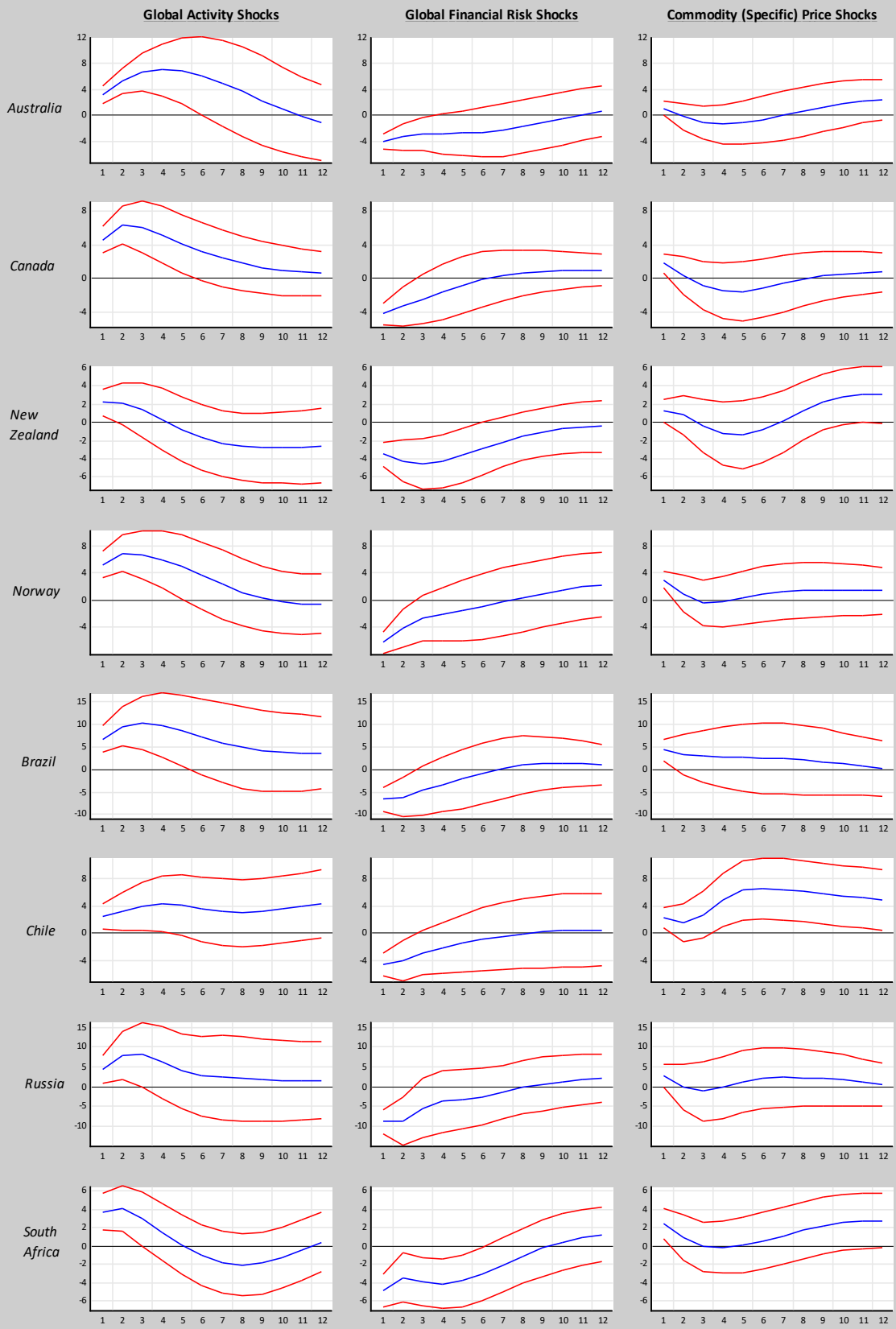
Notes: The figure shows the impulse responses with 95% confidence intervals. The sample period starts in 1995M1 (1996M1 for Brazil) and ends in 2019M12.

Figure 2.14 Real GDP response to global shocks [Robustness - Quarterly data]



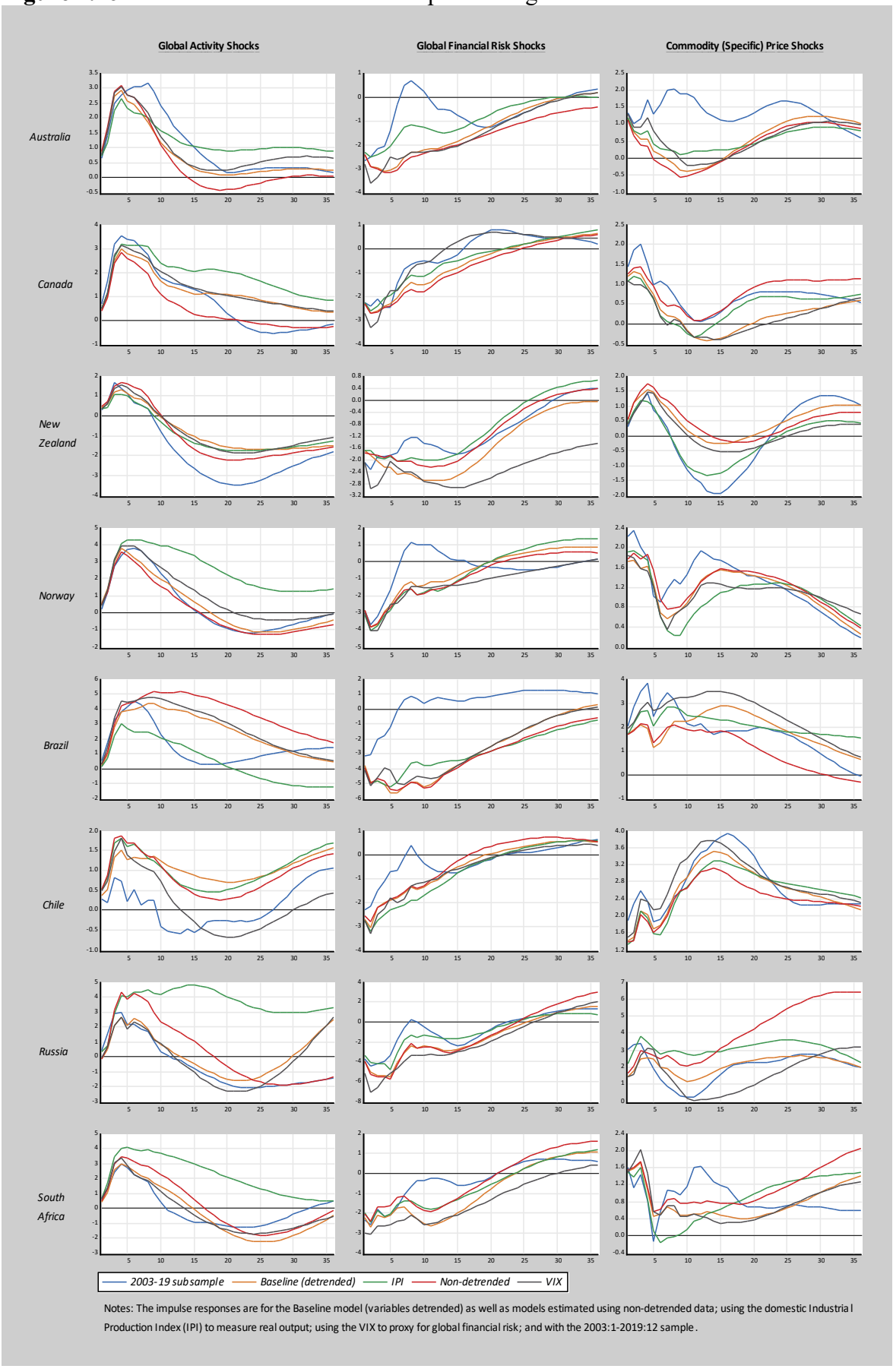
Notes: The figure reports the impulse responses with the 95% confidence intervals. The sample period starts 1995:1 (1996:1 for Brazil) and ends 2019:4.

Figure 2.15 Stock market response to the global shocks [Robustness - Quarterly data]



Notes: The figure reports the impulse responses with the 95% confidence intervals. The sample period starts 1995:1 (1996:1 for Brazil) and ends 2019:4.

Figure 2.16 Robustness of stock market responses to global shocks



Notes: The impulse responses are for the Baseline model (variables detrended) as well as models estimated using non-detrended data; using the domestic Industrial Production Index (IPI) to measure real output; using the VIX to proxy for global financial risk; and with the 2003:1-2019:12 sample.

2.9 Appendix A

A.1. The New-Keynesian small open economy model

Dungey and Pagan (2009) describe a basic New-Keynesian open economy model summarised as follows:

$$\xi_t = \eta_1 \xi_{t-1} + \eta_2 E_t(\xi_{t+1}) + \eta_3 (r_t - E_t \pi_{t+1}) \tag{2.11}$$

$$y_t = a_1 \xi_t + a_2 x_t - a_3 m_t \tag{2.12}$$

$$\pi_t = \eta_4 \pi_{t-1} + \eta_5 E_t(\pi_{t+1}) + \eta_6 (y_t - y_t^n) + \eta_7 E_t \Delta \varsigma_{t+1} + \eta_8 \Delta s_t + u_{Pt} \tag{2.13}$$

$$r_t = \eta_9 r_{t-1} + \eta_{10} (y_t - y_t^n) + \eta_{11} \pi_t + \eta_{12} \varsigma_t + u_{rt} \tag{2.14}$$

$$\varsigma_t = E_t(\varsigma_{t+1}) + (r_t - \pi_t) - (r_t^* - \pi_t^*) + u_{\varsigma t} \tag{2.15}$$

Equations (2.11) – (2.15) represent an IS curve describing absorption (gross national expenditure (GNE)), a log-linearisation of the GDP identity, a Phillips curve, an interest rate rule and a real uncovered interest rate parity (UIP) relationship for the exchange rate, respectively. The variables are represented by ξ_t as the log of absorption (GNE), r_t as the nominal interest rate, π_t as the domestic inflation, y_t as the log of GDP, x_t as the log of exports, m_t as the log of imports, y_t^n as the potential level of output, ς_t as the real exchange rate (quoted so that an increase in ς_t represents an appreciation of the domestic currency), s_t as the log of the terms of trade, r_t^* as the foreign nominal interest rate and π_t^* as the foreign inflation. The error term u_{Pt}, in the Phillips curve represents supply shocks, u_{rt} in the monetary policy reaction function denotes monetary policy shocks, and $u_{\varsigma t}$ is the shock to the UIP relationship.

A.2 Maximum likelihood estimation of SVARs with integrated variables

Estimation of the SVAR model is via the maximum likelihood (ML) estimator. We consider the K-dimensional SVAR model presented in equation (2.5) of the form

$$A_0 y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t = AY_{t-1} + u_t,$$

where $\mathrm{Y}'_{\mathrm{t-1}} \equiv \left(\mathrm{y}'_{\mathrm{t-1}}, \ldots, \mathrm{y}'_{\mathrm{t-p}}\right)$ and $A \equiv \left[A_1, \ldots, A_p\right]$. We assume that the structural shock u_t has a diagonal covariance matrix Σ_u such that $u_t \sim N(0, \Sigma_u)$ and is serially uncorrelated. The associated reduced-form representation is

$$y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + \varepsilon_t = BY_{t-1} + \varepsilon_t,$$

where $B \equiv \left[B_1, \ldots, B_p\right] = A_0^{-1}A$ and the reduced form residual term is $\varepsilon_t = A_0^{-1}u_t \sim N(0, \Sigma_\varepsilon)$ which is assumed to be Gaussian white noise with a positive definite covariance matrix $\Sigma_\varepsilon = A_0^{-1}\Sigma_u A_0'^{-1}$.

The AB-SVAR model of Amisano and Giannini (1997) has the reduced form residuals that have the form

$$A_0 \varepsilon_t = C u_t$$

where $E(u_t) = 0$ and $\Sigma_u = E(u_t u_t') = I_K$ such that $\varepsilon_t \sim N(0, \Sigma_\varepsilon = A_0^{-1}CC'A_0^{-1'})$.

For a sample of $Y \equiv y_1, \ldots, y_T$, the corresponding log-likelihood function that should be maximised can be represented as

$$\begin{aligned} \mathrm{Ln}\, l(A_0, C) = &-\frac{KT}{2}\ln(2\pi) - \frac{T}{2}\ln\left(det\left(A_0^{-1}CC'A_0^{-1'}\right)\right) \\ &-\frac{1}{2}tr\left\{(Y - BZ)\left[A_0^{-1}CC'A_0^{-1'}\right](Y - BZ)\right\} \\ &= constant + \frac{T}{2}\ln(det(A_0)^2) - \frac{T}{2}\ln(det(C)^2) \\ &-\frac{1}{2}tr\left\{A_0'C^{-1'}C^{-1}A_0(Y - BZ)(Y - BZ)'\right\}, \end{aligned} \tag{2.16}$$

where $Z \equiv Y_0, \ldots, Y_{T-1}$, tr denotes the trace of a square matrix (i.e., the sum of its diagonal elements), and matrix rules $det(A_0^{-1}\Sigma_u A_0'^{-1}) = |A_0^{-1}\Sigma_u A_0'^{-1}| = |A_0^{-1}|^2|\Sigma_u|$ and $tr(VW) = tr(WV)$ apply (see Lütkepohl, 2005; Kilian and Lütkepohl, 2017).

With no restrictions on the reduced-form parameters, for any given A_0 and C, the log-likelihood function $ln\, l(A_0, C)$ is maximised with respect to A_0 by

$$\widehat{A_0} = YZ'(ZZ)^{-1} = \left(\sum_{t=1}^{T} y_t Y'_{t-1}\right)\left(\sum_{t=1}^{T} Y_{t-1}Y'_{t-1}\right)^{-1}. \tag{2.17}$$

With $\tilde{\Sigma}_\varepsilon = T^{-1}\sum_{t=1}^{T}\left(Y_t - \widehat{A_0}Z_t\right)\left(Y_t - \widehat{A_0}Z_t\right)'$ the least squares residual, the implied concentrated log-likelihood function is

$$\ln l_c(A_0, C) = constant + \frac{T}{2}ln(det(A_0)^2) - \frac{T}{2}ln(det(D)^2)$$

$$-\frac{1}{2}tr\{A_0'C^{-1'}C^{-1}A_0\tilde{\Sigma}_\varepsilon\}. \quad (2.18)$$

For just-identified SVAR models, the maximum is obtained when $A_0^{-1}\Sigma_u A_0'^{-1} = \tilde{\Sigma}_\varepsilon^{-1}$. If the variances of the structural errors are normalised to one so that $\Sigma_u = I_K$, then the maximum likelihood estimator $\tilde{A}_0$ of A_0 satisfies $\tilde{A}_0^{-1}\tilde{A}_0^{-1\prime} = \tilde{\Sigma}_\varepsilon$ (see Kilian and Lütkepohl (2017) Chapter 9).

A.3 Structural Impulse Response Functions

Structural impulse responses are computed to analyse the dynamic relationships between the variables of interest. Structural impulse response functions (SIRF) indicate how the elements of $\boldsymbol{y_t} = (\boldsymbol{y_{1,t}}, \dots, \boldsymbol{y_{K,t}})'$ respond to an identified structural shock $\boldsymbol{u_{,t}} = \left(\boldsymbol{u_{1,t}}, \dots, \boldsymbol{u_{K,t}}\right)'$,

$$\frac{\partial y_{t+i}}{\partial u_t'} = \Phi_i, \quad i = 0, 1, 2, \dots, H, \quad (2.19)$$

where Φ_i is a $K \times K$ matrix with the $\boldsymbol{jk^{th}}$elements for a given i denoted as

$$\phi_{i,jk} = \frac{\partial y_{j,t+i}}{\partial u_{kt}}, \quad (2.20)$$

where $\boldsymbol{\phi_{i,jk}}$ is the response of the variable j to structural shock k at horizon h. Therefore, an impulse response function (IRF) traces out the time path of the effects of an exogenous shock to an endogenous variable on a variable in a VAR system.

To determine the structural impulse responses, $\boldsymbol{\phi_{i,jk}}$, we can start by identifying the dynamic properties of the VAR from the properties of the vector moving average representation. The responses of y_{t+1} to the reduced-form errors ε_t can be obtained by considering the VAR(1) representation of the VAR(p) process,

$$Y_t = AY_{t-1} + \mathrm{E}_t, \quad (2.21)$$

where

$$Y_t \equiv \begin{pmatrix} y_t \\ \vdots \\ y_{t-p-1} \end{pmatrix}, \qquad A \equiv \begin{bmatrix} A_1 & A_2 & \dots & A_{p-1} & A_p \\ I_K & 0 & & 0 & 0 \\ 0 & I_K & \ddots & 0 & 0 \\ \vdots & & & \vdots & \vdots \\ 0 & 0 & \cdots & I_K & 0 \end{bmatrix}, \qquad \text{and } \mathrm{E}_t \equiv \begin{pmatrix} \varepsilon_t \\ 0 \\ \vdots \\ 0 \end{pmatrix}.$$

Successive substitution for Y_{t-i} in equation (2.21) yields:

$$Y_{t+i} = A^{i+1} Y_{t-1} + \sum_{j=0}^{i} A^j \, \mathrm{E}_{t+i-j}. \tag{2.22}$$

Left-multiplying this equation by $J \equiv \left[I_K, 0_{K \times K(p-1)}\right]$ gives

$$\begin{aligned} y_{t+i} &= JA^{i+1} Y_{t-1} + \sum_{j=0}^{i} JA^j \, \mathrm{E}_{t+i-j} \\ &= JA^{i+1} Y_{t-1} + \sum_{j=0}^{i} JA^j J' J \mathrm{E}_{t+i-j} \\ &= JA^{i+1} Y_{t-1} + \sum_{j=0}^{i} JA^j J' \, \varepsilon_{t+i-j}. \end{aligned} \tag{2.23}$$

The response of the variable $j = 1, \dots, K$ in the VAR(p) system to a unit shock ε_{kt}, $k = 1, \dots, K$, I periods ago is therefore given by

$$\Theta_i = \left[\theta_{jk,i}\right] \equiv JA^j J'$$

where Θ_i is $K \times K$. The Θ_i are the reduced-form impulse responses (also referred to as dynamic multipliers or responses to VAR forecast errors).

The invertibility condition allows a reduced-form VAR to be expressed as an infinite order vector moving average (VMA). Assuming covariance stationarity, y_t can be expressed as a weighted average of current and past shocks, with weights Θ_i that decline, the more distant a shock lies in the past.

Recall that a change in any component of $\boldsymbol{\varepsilon_t}$ represents a weighted average of the same set of structural shocks in the model, with only the weights differing. To replace the reduced-form impulse responses, ε_t, with the structural shocks, u_t, we plug in $\varepsilon_t = A_0^{-1} u_t$, and use the identity $\Phi_i \equiv \Theta_i A_0^{-1}$, obtaining the VMA representation:

$$y_t = \sum_{i=0}^{\infty} \Theta_i \varepsilon_{t-i} = \sum_{i=0}^{\infty} \Theta_i A_0^{-1} A_0 u_{t-i} = \sum_{i=0}^{\infty} \Phi_i u_{t-i} \,. \tag{2.24}$$

Under stationarity, it follows that

$$\frac{\partial y_t}{\partial u'_{t-i}} = \frac{\partial y_{t+i}}{\partial u'_t} = \Phi_i. \tag{2.25}$$

To generate the effects of shocks to the structural innovations on the entire path of y_t we post-multiply Θ_i by $\boldsymbol{A_0^{-1}}$ to obtain:

$$\begin{aligned} \Phi_0 &= \Theta_0 \boldsymbol{A_0^{-1}} = I_k \boldsymbol{A_0^{-1}} = \boldsymbol{A_0^{-1}} \\ \Phi_1 &= \Theta_1 \boldsymbol{A_0^{-1}} \\ \Phi_2 &= \Theta_2 \boldsymbol{A_0^{-1}} \\ &\vdots \end{aligned} \tag{2.26}$$

where Φ_0 is the contemporaneous or instantaneous impact effect of the shock (see Kilian and Lütkepohl, 2017). With a stable VAR, the impulse responses ultimately decay, converging to zero for $h \to \infty$.

A.4 Forecast error variance decompositions

A forecast error variance decomposition indicates the significance of the structural shock $\boldsymbol{u_{k,t}}$ in explaining the forecast error variance of $\boldsymbol{y_{j,t+h}}$ at horizon $\boldsymbol{h}$ is explained by each structural shock $\boldsymbol{u_{k,t}}$. For integrated systems, the FEVD does not converge to the unconditional covariance matrix of y_t as $h \to \infty$ as is the case for a stationary model. Rather, it diverges as the forecast horizon goes to infinity, hence computation is only valid up to a finite maximum horizon of H (Kilian and Lütkepohl, 2017).

The h-step ahead forecast error for a VAR process is

$$y_{t+h} - y_{t+h|t} = \sum_{i=0}^{h-1} \Theta_i \varepsilon_{t+h-i} = \sum_{i=0}^{h-1} \Phi_i u_{t+h-i}\,. \tag{2.27}$$

The forecast error variance or prediction mean squared error (MSPE) at horizon h is

$$\begin{aligned} MSPE(h) \equiv \mathrm{E}\left[\left(y_{t+h} - y_{t+h|t}\right)\left(y_{t+h} - y_{t+h|t}\right)'\right] &= \sum_{i=0}^{h-1} \Phi_i \underbrace{\Sigma_u}_{I_K} \Phi_i' \\ &= \sum_{i=0}^{h-1} \Phi_i \Phi_i' \end{aligned} \tag{2.28}$$

The kj^{th} element of Φ_h is $\boldsymbol{\phi_{i,kj}}$ so that the contribution of shock j to the MSPE of y_{kt}, $k = 1, \ldots, K$, at horizon h is

$$MSPE^k(h) = \sum_{j=1}^{K} MSPE_j^k(h) = \sum_{j=1}^{K} \left(\phi_{kj,0}^2 + \cdots + \phi_{kj,h-1}^2\right), \tag{2.29}$$

and for a given *h* and *k*, dividing by $MSPE^k(h)$ yields the following decomposition:

$$1 = \frac{MSPE_1^k(h)}{MSPE^k(h)} + \frac{MSPE_2^k(h)}{MSPE^k(h)} + \cdots + \frac{MSPE_K^k(h)}{MSPE^k(h)}, \tag{2.30}$$

where each ratio $MSPE_j^k(h)/MSPE^k(h)$ gives the fraction of the contribution of the j^{th} shock to the forecast error variance of variable *k* for $j = 1, \ldots, K$.

A.5 Analytic Asymptotic (Delta) Method Intervals for Structural Impulse Responses

As already mentioned, any VAR model with an intercept and sufficient lags can be consistently estimated in levels, regardless of the presence of unit roots or cointegration (Sims et al., 1990; Kilian and Lütkepohl, 2017).

The asymptotic results based on the delta method for structural impulse response estimates from exactly identified VAR models, as presented by Kilian and Lütkepohl (2017), are summarised as follows. Our VAR(*p*) has the form

$$y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + \varepsilon_t,$$

where y_t is a K-dimensional vector and ε_t is an *iid* error term with at least four finite moments. Under suitable conditions,

$$\sqrt{T}\begin{pmatrix}\hat{\alpha} - \alpha \\ \hat{\sigma} - \sigma\end{pmatrix} \xrightarrow{d} N\left(0, \begin{bmatrix}\Sigma_{\hat{\alpha}} & 0 \\ 0 & \Sigma_{\hat{\sigma}}\end{bmatrix}\right), \tag{2.31}$$

where *T* is the sample size, $\hat{\alpha}$ and $\hat{\alpha}$ denote respectively consistent estimators of $\alpha = vec\left(\left[B_1, \ldots, B_p\right]\right)$ and $\sigma = vech(\Sigma_\varepsilon)$. Assuming block-diagonality of the asymptotic covariance matrix to derive the asymptotic properties of impulse response estimators simplifies the asymptotic distributions. The vec operator denotes a column stacking operator, and the $vech$ operator of a symmetric matrix stacks the elements on and below the main diagonal only.

Each structural IRF coefficient $\phi_{jk,i}$ can be expressed as a component of a continuously differentiable function $g(\alpha, \sigma) = \left(g_1(\alpha, \sigma)\right), \ldots, \left(g_m(\alpha, \sigma)\right)$, where m is the number of structural impulse response coefficients considered. For nonzero partial derivatives $\partial g_i/\partial \alpha'$ and $\partial g_i/\partial \sigma'$ at the true parameter values α and σ for $i = 1, \ldots, m$, the delta method yields

$$\sqrt{T}\big(g(\hat{\alpha},\hat{\sigma})-g(\alpha,\sigma)\big)\xrightarrow{d}N\left(0,\frac{\partial g}{\partial \alpha'}\Sigma_{\hat{\alpha}}\frac{\partial g'}{\partial \alpha}+\frac{\partial g}{\partial \sigma'}\Sigma_{\hat{\sigma}}\frac{\partial g'}{\partial \sigma}\right). \tag{2.32}$$

A requirement of standard asymptotic inference is that the limiting variance is nonzero. Structural IRFs and structural FEVDs involve smooth functions of the form $g(\alpha,\sigma)$. Even if, due to the singularity of $\Sigma_{\hat{\alpha}}$, the leading term $\frac{\partial g}{\partial \alpha'}\Sigma_{\hat{\alpha}}\frac{\partial g'}{\partial \alpha}=0$, the second term, $\frac{\partial g}{\partial \sigma'}\Sigma_{\hat{\sigma}}\frac{\partial g'}{\partial \sigma}$, will always be non-singular, such that the limiting variance of the IRF estimator is non-singular. This validates the use of the delta method for pointwise inference on structural IRFs (and structural FEVDs) in VAR models in levels when the model variables are possibly integrated and/or cointegrated (Kilian and Lütkepohl, 2017).

We are interested in conducting inference on the impulse responses at the horizon step i for the stationary VAR(p) model. Let A_0^{-1} demote the lower triangular (recursive identification) decomposition of Σ_ε such that $A_0^{-1}A_0^{-1\prime}=\Sigma_\varepsilon$. Then we have the following asymptotic results:

$$\sqrt{T}\big(\hat{\Phi}_i-\Phi_i\big)\xrightarrow{d}N(0,\quad C_i\Sigma_{\hat{\alpha}}C_i'+\bar{C}_i\Sigma_{\hat{\sigma}}\bar{C}'_i),\qquad i=0,1,2,\ldots, \tag{2.33}$$

where

$$\begin{aligned}
C_0&=0\\
C_i&=(A_0^{-1\prime}\otimes I_K)\frac{\partial \mathrm{vec}(\Theta_i)}{\partial \alpha'},\qquad i=0,1,2,\ldots\\
\bar{C}_i&=(I_K\otimes \Theta_i)\frac{\partial \mathrm{vec}(A_0^{-1})}{\partial \sigma'},\qquad i=0,1,2,\ldots.
\end{aligned}$$

The sum $C_i\Sigma_{\hat{\alpha}}C_i'+\bar{C}_i\Sigma_{\hat{\sigma}}\bar{C}'_i$ is the covariance of the impulse responses, where $C_i\Sigma_{\hat{\alpha}}C_i'$ reflects the uncertainty associated with the slope parameter estimates and $\bar{C}_i\Sigma_{\hat{\sigma}}\bar{C}'_i$ accounts for the uncertainty associated with the estimate of A_0^{-1}.

The $K^2\times 1$ vector $\sigma_{vec(\hat{\Phi}_i)}$, consisting of the asymptotic standard errors of the elements of $vec\big(\hat{\Phi}_i\big)$, contains the square roots of the elements of the vector

$$\mathrm{diag}(C_i\Sigma_{\hat{\alpha}}C_i'+\bar{C}_i\Sigma_{\hat{\sigma}}\bar{C}'_i).$$

The $diag$ operator stacks the diagonal elements of a square matrix into a column vector. The vector of nominal $(1-\delta)\%$ pointwise asymptotic confidence intervals may be formed as

$$vec\big(\hat{\Phi}_i\big)\pm z_{\delta/2}\hat{\sigma}_{vec(\hat{\Phi}_i)},\qquad i=0,1,2,\ldots,\#(30)$$

where $\hat{\sigma}_{vec(\hat{\Phi}_i)}$ is obtained by replacing the unknowns in $\sigma_{vec(\hat{\Phi}_i)}$ by consistent estimates, and $z_{\delta/2}$ denotes the $\delta/2$ quantile point of the standard normal distribution. The asymptotic standard errors of the structural impulse responses ultimately decline toward zero as the horizon increases.

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3 Economic Growth Risks and Corporate Credit Spreads

3.1 Introduction

Risks associated with macroeconomic conditions are crucial for understanding asset price movements (Chen, 2010). Evidence demonstrates that corporate credit spreads tend to move countercyclically with the economic cycle, widening before and during recessions and narrowing during expansions (Fama and French, 1989; Hackbarth et al., 2006). The number of underperforming firms increases during economic downturns as cash flows decline and become more volatile, raising the risk of corporate distress. Recent research indicates that recessionary periods are associated with increased macroeconomic uncertainty and a negatively skewed distribution of output growth due to heightened downside tail risk (see Adrian et al., 2019; Castelnuovo and Mori, 2025). This chapter examines how macroeconomic risk influences the behaviour of corporate credit spreads, a topic of increasing interest among financial economists, investors, and policymakers.

The U.S. bond market is crucial in financing corporations. Corporate debt levels rose after the 2008 global financial crisis, as companies borrowed more to manage economic shocks and support recovery efforts. Notably, the BAA-rated segment, which is riskier within the investment-grade category, has become the fastest-growing part of this market. A Morgan Stanley (2018) report highlights substantial growth in the BBB-rated portion of investment-grade debt, which increased to about 2.5 times the size of the U.S. high-yield debt market. By 2020, it accounted for about 55% of all investment-grade bonds, up from 33% in 2008 (Acharya et al., 2025).

This increased indebtedness and excessive leverage of investment-grade bonds coincided with a decline in average credit quality, thereby heightening vulnerabilities (Boyarchenko and Shachar, 2020; Acharya et al., 2025). This heightened vulnerability raises concerns about the investment-grade segment's sensitivity to economic shocks. A severe economic downturn could reduce corporate profits and threaten solvency across the

economy, potentially leading to multiple downgrades to high-yield status, which poses risks to the real economy and financial stability. Additionally, declining credit quality increases the risk of significant losses to investors.

A credit spread is a market-based indicator of credit risk that reflects the risk premium investors require to hold corporate debt. Research shows that structural credit risk models based on Merton (1974) do not adequately account for credit spreads on corporate bonds, especially the observed yield difference between investment-grade corporate bonds and Treasuries (e.g., Amato and Remolina, 2003; Huang and Huang, 2012). This discrepancy is known as the credit spread puzzle. The literature has suggested various solutions to address the credit spread puzzle, including incorporating macroeconomic variables into Merton's theoretical framework (e.g., Bhamra et al., 2010a; Chen, 2010).

Many empirical studies examine the link between corporate credit risk and macroeconomic factors, but they mostly focus on growth rates and second moments of economic fundamentals. Risks associated with tail events and higher moments — which economic agents might genuinely prioritise, especially those with asymmetric risk preferences for upside and downside — are often ignored (Adrian et al., 2022). As Bekaert et al. (2021) highlight, asset-pricing models imply that bond risk premiums should be influenced by the expected second and higher moments of macroeconomic variables. Marfè and Pénasse (2024) also note that many macro-finance puzzles arise from the failure of existing theories to quantitatively reconcile asset prices with macroeconomic risks. Furthermore, research by Gabaix (2012) and Gourio (2013) indicates that incorporating time-varying macroeconomic disaster risks into asset pricing models can help resolve the credit spread puzzle. This chapter investigates whether measures of economic growth downside risk, uncertainty, and skewness can explain variations in aggregate investment-grade credit spreads.

Recent economic crises have prompted policymakers to enhance efforts in measuring macroeconomic risks, aiming to inform policies that mitigate the impact of rare but severe shocks on the business cycle (Castelnuovo and Mori, 2025). The existing literature primarily relies on the quantile regression (QR) framework introduced by Koenker and Bassett (1978) (e.g., Adrian et al., 2019; Castelnuovo and Mori, 2025). QR models analyse how covariates affect the conditional quantiles of a response variable, providing a more detailed understanding of its distribution than traditional mean regression models. This approach is especially important when the conditional distribution becomes heavily skewed and exhibits

fat tails. Risk measures derived from quantile regression are particularly valuable for empirical analysis because of their robustness against outliers (Colacito et al., 2016).

We use the monthly growth rate of the U.S. industrial production index (IP growth) as a proxy for the country's output expansion. The industrial production index serves as a key high-frequency indicator of fluctuations in economic output and reliably reflects macroeconomic health. Our analysis covers the period from August 1987 to December 2019. By employing a set of economic and financial indicators as determinants of economic growth, we follow studies such as Ghysels et al. (2018), Adrian et al. (2019), and Castelnuovo and Mori (2025) to derive QR-based IP growth risk measures. Specifically, we construct novel IP growth risk measures, including: (i) growth-at-risk (GaR), (ii) uncertainty (UNC), and (iii) skewness (SKEW).

The *GaR* measure, defined as the conditional growth at the 5th percentile of the IP growth distribution, functions as a downside risk measure that quantifies both the likelihood and severity of adverse outcomes in IP growth. This concept is analogous to the value-at-risk metric used in financial risk management. *UNC* is evaluated using the inter-quantile range, a robust indicator of volatility commonly recognised as a measure of economic risk (Bloom, 2014; Falconio and Manganelli, 2020). The *SKEW* metric assesses the asymmetry of the output growth distribution, capturing the balance between upside and downside risks (Castelnuovo and Mori, 2025).

We define a corporate credit spread as the difference between the yield on a corporate bond and that on a government bond with identical cash flows. This definition indicates that investors are primarily compensated for credit and liquidity risks. We analyse two aggregate investment-grade credit spreads, specifically the yield differentials between Moody's AAA-rated corporate bonds and 20-year Treasury bonds (AAA20Y), and between Moody's BAA-rated corporate bonds and 20-year Treasury bonds (BAA20Y), as our target variables. Our credit spread definitions are consistent with those of Davies (2008) and Krishnamurthy and Vissing-Jorgensen (2012), who argue that the 20-year yield is the natural maturity counterpart to the corporate bonds used in constructing Moody's AAA and BAA indices.

This chapter makes several contributions to the existing literature. More generally, it contributes to a large body of literature on the determinants of corporate bond credit spreads (Collin-Dufresn et al., 2001; Campbell and Taksler, 2003; David, 2008; Cremers et al., 2008). The chapter enriches the recent strand of the literature exploring the macroeconomic determinants of credit risk. For example, studies have considered the role

of GDP growth (Tang and Yan, 2010), inflation (Kang and Pflueger, 2015), and unemployment (Bai, 2021) as determinants of credit risk.

This chapter also contributes to the growing empirical literature highlighting the importance of second- and higher-order moments of macroeconomic fundamentals for explaining asset price dynamics (e.g., Segal et al., 2015; Colacito et al., 2016; Bauer and Chernov, 2024). Studies examining their role in credit spread dynamics remain limited. While studies such as Tang and Yan (2010) and Baum and Wan (2010) have examined the second moment of economic growth, and Kang and Pflueger (2015) have considered inflation volatility, there is a notable paucity of empirical evidence on the role of downside tail risk or skewness.

We construct novel measures of downside risk, uncertainty, and skewness in U.S. output growth to assess their ability to explain U.S. credit spreads. These risk proxies exhibit notable temporal variation and significant movements during crisis periods, such as the 2001 recession and the Great Recession from 2007 to 2009. Furthermore, these risk proxies show substantial correlations with other risk measures proposed in the literature, including the macroeconomic uncertainty indicators estimated by Jurado et al. (2015) and Ludvigson et al. (2021), as well as the skewness measure proposed by Iseringhausen et al. (2023). Our findings provide empirical evidence on the significance of macroeconomic risk in shaping corporate credit spreads, representing a key contribution of this chapter.

Our analysis shows that increases in GaR and UNC risk measures are associated with statistically significant increases in corporate credit spreads, whereas an increase in SKEW narrows aggregate credit spreads. The explanatory power of our novel IP growth risk proxies is both economically and statistically significant across various regression models, regardless of whether control variables are included. Univariate OLS regressions indicate that GaR, UNC, and SKEW are highly significant and explain approximately 16%, 15%, and 18% of the variance in AAA20Y credit spreads, respectively. These figures are even greater for BAA20Y spreads, at around 46%, 40%, and 35%.

We demonstrate that the risk proxies possess additional explanatory power beyond what is accounted for by the first moment of the industrial production index and other credit spread determinants recognised in the existing literature. The statistical significance at the 1% level persists even after controlling for known determinants of credit spreads. Including the GaR or UNC risk measures separately into a baseline regression (which incorporates only control variables) increases the adjusted R^2 of the BAA20Y regression by

approximately 6%. Conversely, the additional explanatory power in the AAA20Y spread regressions is limited to around 1%-2%. The SKEW measure offers an additional 4% in explanatory power for both credit spreads.

Our multiple regression results show that a one-standard-deviation increase in GaR is associated with approximately a 20-basis-point increase in the BAA20Y spread, which is about four times the increase in the AAA20Y credit spread. Similarly, a one-standard-deviation increase in UNC is associated with an 18-basis-point widening of the BAA20Y spread, compared to only 5 basis points for the AAA20Y spread. An increase of one standard deviation in SKEW tends to reduce the AAA20Y spread by roughly 8 basis points and the BAA20Y spread by about 15 basis points. These findings emphasise the greater vulnerability of the more risk-sensitive BAA segment within investment-grade bonds to economic shocks.

Moreover, we conduct regression analyses to assess the persistence of the effects of output growth risk. The findings suggest that the effects of the growth-at-risk (GaR) and uncertainty (UNC) risk metrics on the AAA20Y spread are somewhat transitory. In contrast, they are more persistent for the BAA20Y spread, with statistical significance remaining for up to four months ahead. By contrast, SKEW is more persistent across both spreads, with significant predictive power for the AAA20Y credit spread over 6-month horizons and the BAA20Y spread over 9-month horizons.

We also conduct a series of robustness tests. Our empirical approach lagged industrial production (IP) growth and its associated risk proxies by two months to account for delays in IP data release. While this adjustment helps mitigate endogeneity issues, it may not fully eliminate them. To verify the stability of our main regression results, we use a generalised method of moments (GMM) framework with instrumental variables. We also apply the generalised autoregressive conditional heteroscedasticity (GARCH) model to estimate IP growth volatility and growth-at-risk metrics. The GARCH-based risk proxies demonstrate similar explanatory power to the benchmark results.

Ordinary Least Squares (OLS) models only capture how explanatory variables affect the average outcome. Conversely, quantile regression (QR) examines relationships at different points within the conditional distribution. We therefore adopt the QR approach, which offers a more comprehensive view of how risk proxies relate to the entire distribution of credit spreads. This method enables us to assess how corporate credit spreads respond to economic growth risk during both low- and high-credit-risk periods. Overall, the QR findings align with our OLS results.

Our benchmark analyses only consider investment-grade credit spreads. We also conduct additional analyses across both investment-grade and high-yield bond segments, utilising option-adjusted spreads (OAS). The regression results support our primary findings on how economic growth risks influence credit spreads and emphasise that high-yield debt is more sensitive to macroeconomic risks than investment-grade debt.

Finally, our measures of GaR, UNC, and Skew risk show a strong empirical correlation, prompting the question of whether a single underlying factor influences all of them. We conduct a principal component analysis (PCA) on these three risk measures and identify a main component that accounts for nearly 82% of the total variation in the risk proxies. This first component, used as the measure of macroeconomic risk, is highly positively correlated with credit spreads. A one-standard-deviation increase in this factor is estimated to raise the AAA20Y credit spread by approximately 7.84 basis points and the BAA20Y credit spread by about 21.95 basis points. Including this factor enhances the model's explanatory power, increasing the variance explained in the BAA20Y spread regression by nearly 7.5% and by about 3% in the AAA20Y spread regression. These results emphasise the importance of incorporating macroeconomic risk measures into models for assessing corporate credit-spread risk.

A thorough understanding of the factors that influence credit spreads is crucial for policymakers, investors, and economic researchers, especially given recent economic and financial disruptions. Policymakers closely observe corporate credit spreads for several reasons. As forward-looking indicators, credit spreads reflect investors' expectations of future corporate defaults, making them key leading indicators of economic performance (Gilchrist and Zakrajšek, 2012; Favara et al., 2016). Credit spreads determine the cost of external debt financing for the corporate sector, which, in turn, affects firms' investment decisions and overall economic activity (Bernanke et al., 1999). Institutional investors have different risk attitudes aligned with their investment policies; therefore, they monitor changes in credit spreads. Furthermore, regulators assess the riskiness of credit portfolios when setting capital requirements.

The rest of the chapter is organised as follows. Section 2 presents the theoretical background, related literature, and the development of the hypotheses. Section 3 describes the construction of the risk measures and details the data used in the analyses. Section 4 reports the empirical results, sensitivity analyses, and policy implications. Section 5 concludes.

3.2 Theoretical background, related literature, and hypothesis development

3.2.1 Theoretical background

Aggregate and firm-level outputs are affected by the state of the economy, leading to fluctuations in creditworthiness throughout the business cycle. Bernanke et al. (1999) introduced the financial accelerator framework, which explores how macroeconomic conditions influence corporate defaults. An economic downturn that decreases firms' net worth and current or expected cash flows, thereby lowering asset prices and reducing loan collateral, can lead to reduced bank lending and higher borrowing costs. This, in turn, reduces overall consumption and investment, dampening economic activity. As defaults and bankruptcies increase, credit spreads widen further. However, Gourio (2013) notes that this framework conflicts with empirical evidence showing that credit spreads are often larger than those implied by default losses alone (calculated as the product of default probability and loss given default).

The structural credit risk model, introduced by Merton (1974), suggests that a firm's equity and debt can be seen as contingent claims on the value of the firm’s underlying assets. In this model, equity holders are considered to hold a portfolio consisting of a long position in the firm’s assets, a short position in a risk-free bond, and a long position in a put option on the firm's assets. Likewise, holding a corporate bond is economically equivalent to a portfolio that includes a long position in a risk-free bond and a short position in a put option on the firm’s assets, with the option’s strike price set at the risk-free bond's face value.

The put option reflects the limited liability of equity holders in the event of bankruptcy, as they are the residual claimants on the firm’s assets after debt holders have received their promised cash flows. In the event of default, the equity holder may exercise the put option, thereby transferring the firm's assets to the debt holder. The firm's assets typically have a value lower than the risky debt’s value, which is the “recovery rate” associated with the risky bond.

Assuming perfect and complete markets with continuous trading, a credit spread primarily compensates for credit risk, which equals the probability of default multiplied by the expected loss given default. However, when structural default risk models are calibrated to historical default data and the equity risk premium typical of investment-grade corporate debt, credit risk tends to underpredict actual investment-grade corporate-Treasury spreads

(Huang and Huang, 2012), a phenomenon known as the credit puzzle. Some scholars argue that this occurs because the core assumptions of the standard Merton (1974) model may be too restrictive. Others contend that additional relevant factors beyond credit risk are missing.

A growing body of theoretical research explicitly incorporates the macroeconomic environment within Merton's (1974) framework. These studies demonstrate that credit risk premiums are affected by broad macroeconomic conditions, as shown by Chen et al. (2009) and Bhamra et al. (2010a, 2010b). Furthermore, Hackbarth et al. (2006) argue that firms adjust their default and financing strategies in response to the economy's cyclical phases, since cash flows depend on prevailing economic conditions, thereby incorporating macroeconomic dynamics into dynamic capital structure and credit risk models.

Bhamra et al. (2010a) examine how time-varying macroeconomic risks influence capital structure by integrating the traditional structural model of debt and capital structure with a consumption-based asset-pricing model. This enables them to investigate how macroeconomic risk affects optimal corporate finance strategies, the link between leverage and default probability, and how investor preferences shape leverage and default decisions. In their later work, Bhamra et al. (2010b) incorporate the structural model within a representative-agent consumption-based framework. Their approach connects the equity risk premium, the term structure of credit spreads, and endogenous default probabilities to time-varying macroeconomic risks.

Chen (2010) develops a dynamic capital structure model to analyse how macroeconomic conditions influence corporate financing and default decisions. The model incorporates time-varying expected growth rates, economic uncertainty, and risk premia, providing a comprehensive explanation for the countercyclical co-movements observed among risk prices, default probabilities, and default losses. According to Chen's model, marginal utility rises during recessions, prompting investors to demand higher premiums for credit risk. Additionally, the model recognises that corporate cash flows may decrease during recessions, leading to greater volatility and a stronger correlation with market fluctuations.

An alternative to the structural credit risk model is the reduced-form framework introduced by Jarrow and Turnbull (1995), which models default probability as an intensity process. While structural models directly connect default to firm value, reduced-form models do not explicitly associate the default event with the firm's economic conditions. Therefore, unlike the structural credit risk model, default is regarded as exogenous in a reduced-form model, without making any assumptions about the origin of the credit risk premium.

A related body of literature investigates the asset-pricing implications of disaster risk, suggesting that rare disasters help explain the size of the default spread. Gourio (2013) embeds a capital structure model within a general equilibrium framework that incorporates exogenous disaster risk to capture the possibility of an extremely severe recession. The rare-disaster model of Christoffersen et al. (2017) incorporates a reduced-form default-risk model within a habit-formation framework. This captures the empirical level and volatility of investment-grade credit spreads.

3.2.2 Related literature

3.2.2.1 ***Literature on the determinants of credit spreads***

The Merton (1974) structural model suggests that credit spreads should be a function of the risk-free interest rate, the nominal outstanding debt, the firm's leverage, and asset volatility. Collin-Dufresne et al. (2001) demonstrate that the variables theoretically expected to explain changes in credit spreads have limited explanatory power, leaving a significant unexplained portion mainly driven by factors unrelated to credit risk and standard liquidity measures. Elton et al. (2001) and Huang and Huang (2012) show that credit risk accounts for only a small part of the observed credit spreads for investment-grade bonds.

Campbell and Taksler (2003) find that idiosyncratic volatility can explain about one-third of yield spreads for investment-grade bonds rated below AAA. Gemmill and Keswani (2011) find that the level of credit spreads is strongly related not only to idiosyncratic equity volatility, but also to idiosyncratic bond volatility and idiosyncratic bond value-at-risk.

Many studies investigating the credit spread puzzle consider factors beyond default risk. For instance, some research examines the effect of differential illiquidity (e.g., Longstaff et al., 2005; Chen et al., 2007) and differences in tax treatment between corporate bonds and Treasury securities (e.g., Elton et al., 2001).

A key area of current research explores the relationship between the credit spread puzzle and macroeconomic factors. Fama and French (1989) and Chen (1991) highlight that credit spreads tend to be countercyclical. Recent studies, including those by Tang and Yan (2010) and Chun et al. (2014), demonstrate that credit spreads move inversely with GDP or industrial production growth. Bai (2021) identifies a positive correlation between unemployment rates and corporate credit spreads. Furthermore, macroeconomic risk significantly influences corporate financing decisions (e.g., Hackbarth et al., 2006), which are vital for understanding credit spreads.

Kang and Pflueger (2015) find that inflation volatility can explain as much or more variation in credit spreads than equity volatility and the dividend-price ratio. Tang and Yan (2010) demonstrate that credit spreads also increase with volatility in GDP growth. Kaviani et al. (2020) find that policy uncertainty has significant explanatory power for corporate credit spreads.

3.2.2.2 Literature on macroeconomic risks

The chapter draws on the literature examining tail risks in macroeconomic outcomes. Notable among these studies is Adrian et al. (2019), who use quantile regression to characterise both upside and downside risks to GDP growth. Adrian et al. (2019) demonstrate that downside risk to output growth, referred to as growth-at-risk and measured by the 5% quantile of a predictive GDP distribution, fluctuates significantly over time, whereas upside risk remains stable.

A substantial body of research examines the financial and economic impacts of uncertainty. Empirical evidence shows that macroeconomic uncertainty tends to be countercyclical, rising during recessions and falling during periods of growth (e.g., Bloom, 2014; Castelnuovo and Mori, 2025).

The macroeconomic literature shows that macroeconomic risks tend to be asymmetric around the baseline outlook, with the conditional distributions of economic variables exhibiting skewness (Adrian et al., 2019; Iseringhausen et al., 2023). The skewness of output growth, an important indicator of the distribution of tail risks, exhibits temporal fluctuations (Jensen et al., 2020) and is pro-cyclical (Iseringhausen et al., 2023; Castelnuovo and Mori, 2025). Iseringhausen et al. (2023) and Castelnuovo and Mori (2025) derive measures of skewness using estimated quantiles from the conditional distribution of GDP growth.

3.2.2.3 Literature on the effects of second and higher-order moments

This chapter also relates to the literature on the information content of second and higher-order moments. Fluctuations in macroeconomic uncertainty influence the decision-making of firms and individuals, with increased uncertainty leading to significant declines in household expenditure, investment, output, and asset values (Bloom, 2014; Jurado et al., 2015; Ludvigson et al., 2021; Castelnuovo and Mori, 2025).

Tang and Yan (2010) document a positive correlation between credit spreads and the volatility of economic growth rates. Baum and Wan (2010) examine the impact of

macroeconomic uncertainty on credit default swap spreads, highlighting substantial explanatory power beyond traditional macroeconomic indicators, such as the risk-free rate and the Treasury term spread. Kang and Pflueger (2015) show that credit spreads tend to rise in response to inflation volatility, while a low-inflation environment subsequently mitigates credit risk.

Investors generally exhibit a strong aversion to negative skewness, which indicates greater downside tail risk and thus requires additional compensation. Gemmill and Keswani (2011) contend that idiosyncratic bond value-at-risk helps explain credit spreads because it captures the left skewness of the firm-value distribution. Bauer and Chernov (2024) demonstrate that the conditional skewness of Treasury yields has significant predictive power for future bond excess returns and high-frequency interest rate fluctuations. Colacito et al. (2016) find that the time-varying skewness in the distribution of expected GDP growth is both economically and statistically important in forecasting future equity excess returns.

A related body of literature investigates the implications of rare disaster risk. Disasters are characterised as low-probability events that cause significant drops in output or consumption, leading to fat-tailed, left-skewed distributions (Gormsen and Jensen, 2022). Gabaix (2012) and Gourio (2013) explore how time-varying disaster severity affects asset pricing, showing that the rare-disaster risk framework can help explain the credit spread puzzle. Gourio (2013) argues that the risk premium on corporate bonds compensates for bearing tail risk (i.e., low-probability events with catastrophic outcomes), and this exposure varies considerably across different phases of the business cycle.

3.2.2.4 ***Hypothesis development***

Recessions are linked to declines in consumption, investment, output, corporate profits, and asset prices. Several asset-pricing studies have highlighted how risk aversion and risk premia change over time. Empirical evidence suggests that corporate credit spreads are notably countercyclical (Hackbarth et al., 2006), with most defaults and low recovery rates occurring during severe economic downturns. The significant widening of credit spreads in these periods can be explained by a cash-flow effect (where expected payments to debt holders decrease), a discount-rate effect (due to lower consumption and increased marginal utility), or a combination of both (Miao and Wang, 2010).

The time-variation and countercyclicality of risk aversion (Campbell and Cochrane, 1999) are associated with investors' asymmetric risk preferences (e.g., Kahneman and Tversky, 2013; Gul, 1991; Augustin and Tédongap, 2021). According to prospect theory,

proposed by Kahneman and Tversky (2013), investors respond asymmetrically, showing greater sensitivity to losses than to gains due to their inherent aversion to losses. Similarly, the theory of disappointment aversion, introduced by Gul (1991), suggests that economic agents place more importance on unfavourable outcomes than on favourable ones.

Standard finance theory suggests that assets that provide low returns during tough economic times are considered unattractive because they tend to yield smaller payoffs as investor wealth declines. The attractiveness of corporate bonds declines in economic downturns, when investors become more risk-averse. This leads to higher risk premiums and increasing credit spreads (Fama and French, 1989; Campbell and Cochrane, 1999; Gourio, 2013). Additionally, a rise in risk can trigger a flight to safety, during which the prices of "safe and liquid" Treasury bonds increase due to heightened demand. Conversely, corporate bond prices tend to fall, further widening credit spreads.

Merton (1974) conceptualises equity as a long call on firm assets and bonds as a short put. This framework suggests that credit spreads tend to narrow as firm asset values increase and widen with asset volatility. During severe economic downturns, characterised by high marginal utilities and falling asset values, default rates generally rise while recovery rates fall. Under such conditions, corporate bond investors require higher risk premiums, leading to wider credit spreads. We therefore hypothesise that:

Hypothesis 1: Increasing downside tail risk to economic growth is positively correlated with corporate credit spreads.

Recessions are periods characterised by increased economic uncertainty and rising marginal utility for investors. Chen (2010) suggests that greater economic uncertainty makes a firm's cash flows more correlated with market fluctuations, thereby increasing the likelihood of default. As a result, investors require a higher risk premium to compensate for the increased risk. Additionally, Bloom (2014) argues that uncertainty intensifies the risk of negative outcomes for firms, leading to higher default probabilities and, consequently, wider credit spreads. We therefore test the hypothesis that:

Hypothesis 2: Output growth uncertainty has a positive relation with aggregate credit spreads.

The skewness measure reflects the imbalance between upside and downside risks to growth. As noted earlier, default probabilities tend to rise during recessions, when downside risks to output are greater. Typically, firms increase leverage during economic booms, as improved cash flows and higher credit ratings reduce borrowing costs. These periods often see heightened risk appetite and greater risk-taking, which can lead to a buildup of financial

vulnerabilities. If economic conditions worsen, defaults may cluster, prompting investors to demand wider yield spreads. Therefore, the following hypothesis is proposed:
Hypothesis 3: Credit spreads decrease with the skewness of output growth.

3.3 Data and methodology

This section details the methodology and data for our empirical analysis. First, we explain how we derive the proxies for output growth risk. Next, we review the credit spread dataset and the control variables used, along with their summary statistics.

3.3.1 Variable construction

The QR framework proposed by Koenker and Bassett (1978) has become the standard methodology for assessing risks to economic outcomes. This framework enables estimation of conditional quantiles of the economic variable's distribution, thereby facilitating the quantification of downside (lower tail) and upside (upper tail) risks (Adrian et al., 2019). In the spirit of Ghysels et al. (2018) and Castelnuovo and Mori (2025), we construct measures to evaluate downside tail risk, uncertainty, and skewness risk associated with industrial production growth.

3.3.1.1 ***Quantile regression***

The QR approach extends the OLS model, which estimates the effect of explanatory variables on the conditional mean of the response variable, to analyse their impact across different quantiles.[8] It can therefore identify potential nonlinear relationships between shocks to the covariates and extreme IP growth observations.

Let us assume a least-squares model where the current IP growth is linearly linked to a vector of lagged conditional variables, x_{t-1}, as follows:

$$\Delta IP_t = \beta' x_{t-1} + u_t \quad \text{for } t = 1, \dots, T-1. \tag{3.1}$$

x_{t-1} is the vector of k lagged predictors (also including the lag of Δip_t) plus the intercept term, and u_t is an $i.i.d$ mean-zero sequence. QR assumes a linear relationship between the predictors and the quantile function of some outcome variable. The τ-th conditional quantile of IP growth is a linear function of x_{t-1} given by

$$Q_\tau(\Delta IP_t | x_t) = \beta' x_{t-1} + Q_\tau(u) \tag{3.2}$$

[8] Please refer to the appendix for a detailed description of the quantile regression approach.

where β' is the vector of regression slopes and $Q_\tau(u)$ is the quantile function of u_t (Koenker and Bassett, 1978). The regression slopes $\hat{\beta}(\tau)$ are obtained by minimising the quantile-weighted absolute value of errors:

$$\hat{\beta}(\tau) = \underset{\beta \in R^k}{argmin} \sum_t \omega_t(\tau) |\Delta IP_t - \beta(\tau)' x_{t-1}| \tag{3.3}$$

with weights

$$\omega_t(\tau) = \underset{\beta \in R^k}{argmin} \begin{cases} \tau & \text{if } \Delta IP_t \geq x_{t-1}\beta \\ (1-\tau) & \text{if } \Delta IP_t < x_{t-1}\beta. \end{cases} \tag{3.4}$$

The QR approach has several desirable properties. Its semiparametric nature removes the need for homoscedasticity and eliminates the requirement to make explicit assumptions about the error term's distribution, such as assuming a Gaussian distribution. Additionally, QR estimators are less sensitive to outliers than least-squares estimators. This is because the local behaviour of the conditional distribution of the response variable near the specified quantile mainly influences quantile estimation. This feature is especially beneficial since many datasets exhibit non-normal distributions with heavy tails (Lee and Lee, 2015).

3.3.1.2 ***Constructing the IP growth risk measures***

Industrial production growth is measured by the continuously compounded rate of change in the seasonally adjusted industrial production (IP) index (that is, $ln(IP_t/IP_{t-1}) * 100$). The data are sourced from the Federal Reserve Bank of St. Louis' FRED database.

Empirical research has identified several variables as determinants of economic growth. Economic dynamics change in volatile economic regimes, implying that variables which seem insignificant during stable periods can become important during recessions. Therefore, the impact of predictors on output growth may depend on the quantile being analysed (Prüser and Huber, 2024). As a result, we consider a set of candidate tail-risk predictor variables identified in the literature, whose significance might vary across different quantiles.

The seminal study by Adrian et al. (2019) uses the Chicago Fed's National Financial Conditions Index (NFCI) to assess GDP growth-at-risk. However, Corradi et al. (2020) suggest that alternative predictors are more informative when using higher-frequency monthly industrial production data. Table 3.1 describes the variables and data sources.

Some studies in the literature suggest averaging predictions from multiple models when the actual data-generating process is unknown. This method considers all information

provided by different models and has outperformed reliance on any single model (e.g., Cook and Doh, 2019). Therefore, we examine the following four specifications that utilise various predictor variables:

- *Model 1:* lagged IP growth, monthly sum of the Aruoba, Diebold, and Scotti (2009) business conditions index (ADS index), monthly sum of the NFCI, the Chicago Fed National Activity *Index* (*CFNAI*), and the change in the 10-year Treasury Constant Maturity Rate (GS10).[9]
- *Model 2:* lagged IP growth, ADS index, S&P500 returns, and the unemployment gap.[10]
- *Model 3:* lagged IP growth, ADS index, unemployment gap, and the change in the GS10.
- *Model 4:* lagged IP growth and the ADS index.[11]

3.3.1.3 The economic growth risk proxies

For each model, $m = \{1, 2, 3, 4\}$, we estimate the $\tau = \{0.05, 0.5, 0.95\}$ conditional quantiles. The 5th and 95th conditional quantiles measure the downside and upside risks of industrial production growth, respectively. We evaluate the accuracy of the quantile estimates by comparing the frequency with which IP growth exceeds the τ-th conditional quantile with the expected number of violations. Additionally, we perform the Unconditional Coverage (UC) backtest proposed by Kupiec (1995) and the Conditional Coverage (CC) backtest introduced by Christoffersen (1998). The UC test checks whether the proportion of actual violations aligns with the nominal τ level. Rejecting the null hypothesis that the unconditional probability of violation equals τ suggests that the quantile regression (QR) model may be misspecified. The CC test, on the other hand, examines both the frequency of violations and whether they occur independently over time.

Table 3.2 illustrates the effectiveness of our Quantile Regression (QR) framework in estimating conditional quantiles. The observed violations closely align with the expected number. The results from the two backtests, UC and CC, are assessed at the 5% significance

[9] The ADS, NFCI, and CFNAI indices employed by Barbaglia et al. (2023) are indicators that summarise information about a wide array of economic and financial variables that proxy well for the state of the economy. We use the monthly sum of the Aruoba-Diebold-Scotti Business Conditions Index and the Chicago Fed National Financial Conditions Index.

[10] We follow Atanasov (2021) to measure the unemployment gap as a residual resulting from a cubic time trend model.

[11] Non-stationary predictor variables are differenced to attain stationarity.

level. All *p*-values exceed 5%, indicating that the QR framework is well specified and yields reliable conditional quantile estimates.

The risk measures are then constructed as follows:

Growth-at-risk (GaR). We define growth-at-risk as the 5th conditional quantile of the IP growth distribution. The growth-at-risk measure monitors downside risk to output growth in macroeconomics (Adrian et al., 2019; Plagborg-Møller et al., 2020). *GaR* is given by:

$$GaR_t^m = -1 * \hat{Q}_{0.05}(\Delta IP_t | x_{t-1}) \tag{3.5}$$

where $i = \{Model\ 1, Model\ 2, Model\ 3, Model\ 4\}$. We multiply by minus one following the convention in finance, so that an increase in *GaR* indicates heightened downside risk.

Uncertainty (UNC). The inter-quantile range is considered a robust proxy for uncertainty (Ghysels et al., 2018).[12] It measures the spread between selected quantiles of the conditional density of output growth. UNC is defined as follows:

$$UNC_t^m = \hat{Q}_{0.95}(\Delta IP_t | x_{t-1}) - \hat{Q}_{0.05}(\Delta IP_t | x_{t-1}) \tag{3.6}$$

An increase in this uncertainty measure indicates a greater likelihood of extreme realisations in industrial production (IP) growth.

Skewness (SKEW). Following Ghysels et al. (2018), we construct a measure of IP growth skewness based on Hinkley's (1975) robust measure of asymmetry, which is defined as follows:

$$SKEW_t^m = \frac{\hat{Q}_{0.95}(\Delta IP_t | x_{t-1}) + \hat{Q}_{0.05}(\Delta IP_t | x_{t-1}) - 2 * \hat{Q}_{0.50}(\Delta IP_t | x_{t-1})}{\hat{Q}_{0.95}(\Delta IP_t | x_{t-1}) - \hat{Q}_{0.05}(\Delta IP_t | x_{t-1})} \tag{3.7}$$

This measure assesses whether the time-varying conditional distribution has greater upside potential than downside risk. Positive values indicate a right-skewed distribution, signifying higher upside risks, while negative values point to vulnerable growth (greater downside risks), which is typical during periods of recession.

Averaging the risk proxy measures. In the previous step, we calculated risk measures for each of the competing models. We summarise this information by taking simple, equal-weighted averages of the metrics derived from the four models as follows:

[12] Taylor (2005) argues that if the left and right tails of the conditional distribution are influenced by different forces over time, the inter-quantile range should better capture the evolution of variance than GARCH models, which use only an autoregressive model for the variance.

$$RP_t = \frac{1}{4}\sum_{m=1}^{4} RP_t^m \quad (3.8)$$

where $RP_t^m = \{GaR_t^m, UNC_t^m, SKEW_t^m\}$. We choose simple averaging primarily due to its computational ease and because empirical studies indicate it performs similarly to more sophisticated combination techniques (Taylor, 2020).

3.3.2 Dependent variables

Our empirical analysis investigates monthly aggregate U.S. investment-grade credit spreads. The sample period begins with Alan Greenspan's appointment as Chair of the U.S. Federal Reserve in August 1987, highlighting his focus on risk management as a key aspect of monetary policy, and continues through December 2019.

We define a credit spread as the yield difference between a corporate bond and a government bond with the same maturity. Following Davies (2008) and Krishnamurthy and Vissing-Jorgensen (2012), we use the 20-year Constant Maturity Treasury yield. They argue that this yield is the most suitable government benchmark for maturity, corresponding to the yields on Moody's Aaa- and Baa-rated corporate bonds, which typically have maturities of at least 20 years. We define two measures of aggregate investment-grade credit spreads as follows:

- *AAA20Y credit spread*: Moody's Aaa-rated bonds represent the highest quality (lowest default risk) within the investment-grade segment of the U.S. credit market. The AAA20Y spread mainly reflects liquidity and tax differences between corporate and Treasury bonds.
- *BAA20Y credit spread:* Moody's Baa-rated bonds are riskier and less liquid than Aaa-rated obligations. In addition to default risk, the BAA20Y spread reflects safety and liquidity premiums (Krishnamurthy and Vissing-Jorgensen, 2012) as well as tax effects.

Figure 3.1 shows the time series of the two credit spreads. Both spreads exhibit countercyclical behaviour, widening before and during economic downturns and narrowing during periods of economic growth. Throughout the sample period, the credit spreads display no significant upward or downward trend.

3.3.3 Control variables

Drawing from prior empirical studies, we consider these factors as key determinants of credit spreads:

(i) Growth in industrial production (*IP growth*) indicates a positive phase in the business cycle, signalling economic expansion. Such conditions are associated with rising asset values and potentially higher recovery rates. Assuming other factors remain constant, this may lead to higher corporate debt prices, a lower likelihood of default, and narrower corporate credit spreads (Davies, 2008; Tang and Yan, 2010).

(ii) The monthly return of the S&P 500 index ($\Delta SP500$) is used as an indicator of overall economic health and also the economic recovery rate (Collin-Dufresne et al., 2001; Tang and Yan, 2010). Furthermore, Collin-Dufresne et al. (2001) suggest that stock returns can serve as a measure of leverage. Generally, asset values tend to increase as equity market performance rises, which should lead to a decrease in leverage. When asset values are high relative to debt levels, firms are less likely to default and therefore have narrower yield spreads (see, e.g., Collin-Dufresne et al., 2001; Campbell and Taksler, 2003; Davies, 2008). Consequently, we expect a negative correlation between stock market returns and credit spreads.

(iii) The nominal 3-month Treasury bill (*T-bill*). The structural framework shows that an increase in the risk-free rate raises the risk-adjusted drift of firm value, keeping the firm value above the default threshold. As a result, this dynamic lowers the price of the put option, reduces the risk of default, and consequently tightens credit spreads (Longstaff and Schwartz, 1995; Ericsson et al., 2009). This indicates a negative relationship between the risk-free rate and credit spreads.

(iv) Slope of the Yield Curve (*Slope*). This measure acts as an indicator of overall economic health (Collin-Dufresne et al., 2001). The Treasury slope is the difference between the ten-year and three-month U.S. Treasury yields (Bai, 2021). It reflects expectations about future short-term interest rates. According to the expectations theory of interest rates, a negative slope of the yield curve indicates a diminishing maturity premium, which may suggest a weakening economy. We hypothesise that the Treasury slope is negatively related to credit spreads.

(v) The VXO index. Merton (1973) suggests that the market value of corporate debt resembles a short position in a put option on the firm's overall value. We anticipate a positive relationship between asset volatility and the credit spread, as the value of the put option increases with increased volatility. Specifically, an uptick in expected volatility reflects higher market risk and, consequently, a greater likelihood of default.[13]

[13] The VXO index is a measure of implied volatility of a hypothetical 30-calendar-day at-the-money option on the S&P 100 index (OEX). It is sourced from the FRED database and log transformed.

(vi) Consumer sentiment (*Sentiment*). Variations in credit spreads can indicate households' capacity to bear risks. Consumer confidence generally rises during economic expansions, which are characterised by decreasing credit spreads, whereas it falls during economic contractions, when credit spreads tend to widen sharply (Tang and Yan, 2010). We utilise the log-transformed University of Michigan's Consumer Sentiment Index, obtained from the Federal Reserve Economic Data (FRED).[14]

3.3.4 Descriptive statistics

3.3.4.1 ***Industrial production risk proxies***

Figure 3.2 illustrates how measures of economic growth risk fluctuate over time. Panel (a) shows the time series of the 5th percentile, IP growth, and the 95th percentile. The 5th percentile shows considerably greater volatility than the 95th percentile (which signifies upside risk), consistent with Adrian et al. (2019). It indicates that downside risks to output growth rise sharply during downturns and recessions, and decrease during periods of economic expansion.

Panel (b) of Figure 3.2 shows the time series of the UNC estimate. This demonstrates that macroeconomic uncertainty generally increases during periods of weak growth, highlighting its countercyclical nature, as noted by Jurado et al. (2015). Consistent with Castelnuovo and Mori (2025), our uncertainty proxy has a correlation coefficient of 0.69 with the macroeconomic uncertainty index but only 0.41 with Ludvigson et al.'s (2021) financial uncertainty index.

The constructed measure of skewness, SKEW, is shown in panel (c). It fluctuates significantly over time in a procyclical pattern. This asymmetry reflects the changing balance between upside and downside risks, as displayed in panel (a). Positive skewness signifies a dominance of upside risks over downside risks, which is common during expansion phases of the cycle. Conversely, negative skewness indicates greater downside risk to economic growth. Skewness was predominantly negative during the recessions of 1990-91, 2001, and 2008, when downside risks to economic growth were heightened. Our skewness proxy correlates with the macroeconomic skewness measure by Iseringhausen et al. (2023), with a coefficient of 0.47.

[14] See Table 3.1 for data sources.

3.3.4.2 ***Summary statistics***

Table 3.3 summarises the credit spreads, risk proxies and control variables.[15] Panel (a) displays summary statistics for the dependent variables and covariates. Stock returns are calculated as the log difference of the monthly S&P 500 index. The monthly S&P 500 index is derived as the arithmetic mean of daily returns over the month. The VXO and the University of Michigan Consumer Sentiment Index are both log-transformed.

The mean of the BAA20Y spread is roughly 100 basis points (bps) higher than that of the AAA20Y spread. The BAA20Y spread distribution is leptokurtic and exhibits nearly five times the positive skewness of the AAA20Y spread distribution. Moreover, unit root tests indicate that both credit spreads are stationary, consistent with economic expectations of mean reversion (Cremers et al., 2008; Doshi et al., 2013).

Panel (B) of Table 3.3 shows the univariate correlations among the regression variables, indicating that credit spreads are negatively correlated with IP growth, GaR, and SKEW, and positively correlated with UNC. The inverse relationship between UNC and IP growth emphasises the countercyclical behaviour of uncertainty, which typically rises during periods of slowing economic growth.

The correlations between GaR and the UNC and SKEW measures are notably high (0.91 and -0.67, respectively); therefore, we exclude GaR from regression analyses involving UNC and SKEW to prevent multicollinearity issues. The data clearly demonstrate a relationship between credit spreads and the risk proxies, with the BAA20Y spread exhibiting higher correlations (62% to 71%) than the AAA20Y spread (44% to 51%).

The AAA20Y and BAA20Y credit spread time series show significant persistence, with autocorrelation coefficients of 0.96 and 0.95, respectively. Among the risk proxies, SKEW has the lowest autocorrelation coefficient at roughly 0.5, while GaR and UNC have AR(1) coefficients of 0.88 and 0.71, respectively. The 3-month T-bill rate and the Treasury slope exhibit the highest AR(1) coefficients, at 0.995 and 0.98, respectively.

[15] Where required we seasonally adjust time series using the X-13ARIMA-SEATS procedure.

3.4 Empirical results

3.4.1 Empirical methodology

We investigate whether measures of output growth risk can significantly explain fluctuations in corporate credit spreads. Our approach builds on research by Campbell and Taksler (2003) and Cremers et al. (2008), which focus on credit spread levels. Cremers et al. (2008) contend that, from an economic perspective, credit spreads should not follow a unit root process because they reflect ex ante expected return differentials. Doshi et al. (2013) support this view, maintaining that credit spreads are stationary since, unlike stock prices or aggregate consumption, they are not fundamentally characterised by a positive drift.

Differencing is preferred when the dependent variable and regressors are integrated to avoid spurious regression. Unit root test results in Table 3.3 indicate that the AAA20Y and BAA20Y credit spreads, along with most control variables, are stationary.[16] First-differencing a stationary time series may inadvertently introduce noise into the regression results. Our baseline regression model is therefore specified in levels as follows:

$$CS_t = \alpha + \beta RP_{t-2} + \gamma_1 IPGrowth_{t-2} + \gamma_2 LogVXO_t + \gamma_3 Sentiment_t + \gamma_4 r_t + \gamma_5 Tbill_t + \gamma_6 TS_t + \varepsilon_t \quad (3.9)$$

where at the time t, $CS_t = \{AAA20Y_t, BAA20Y_t\}$ and $RP_t = \{GaR_t, UNC_t, SKEW_t\}$. We are limited to this set of covariates to avoid multicollinearity issues.[17]

Since the primary aim of this chapter is to explain credit spreads rather than predict them, we employ contemporaneous dependent and explanatory variables. Exceptions are industrial production (IP) growth and the risk proxy variables, which are lagged by two months to account for publication delays and substantial revisions in the IP data. This approach ensures that IP data consistently form part of the information set available to investors in real time (Atanasov, 2021). Additionally, it addresses endogeneity arising from bidirectional causality between macroeconomic variables and credit spreads (Oikonomou et al., 2014).

[16] Unit root tests reported in Table 3.3 suggest the 3-month Treasury yield is non-stationary. However, the levels regressions should still yield consistent point estimates (see Ericsson et al., 2009).

[17] Financial variables tend to be highly correlated with each other; therefore, we could not include in the regressions the 10-year government bond yield or the difference between yields on the 10-year swap index and 10-year Treasuries as proxies for the long rate and liquidity, respectively (see Collin-Dufresne et al., 2001).

3.4.1.1 ***OLS regression results***

Table 3.4 shows the coefficient estimates and *t*-statistics for the baseline regression in equation (3.9). In Panel A, the AAA20Y spread is the dependent variable, while Panel B investigates the BAA20Y spread. Multicollinearity is not a significant concern, as the variance inflation factors (VIFs) are below 3 for the output growth risk proxies and under 5 for the control variables.

Columns (2) to (4) show the univariate regression results for the models using GaR, UNC, and SKEW risk measures, respectively. As expected, there is a positive relationship between credit spreads and the GaR and UNC risk metrics. Conversely, an increase in SKEW, which indicates upside risks, is associated with a decrease in credit spreads. All coefficients for the output growth risk indicators are highly significant at the 1% level or better. The adjusted R^2 values for regressions with GaR, UNC, and SKEW explain approximately 16%, 15%, and 18% of the variation in the AAA20Y credit spread, respectively. These percentages are higher for the BAA20Y credit spread, which accounts for roughly 46%, 40%, and 35% of the variance, respectively.

There are concerns that the output growth risk proxies may reflect various factors, such as market uncertainty and investor sentiment. Column (1) shows the results of our baseline regression with only control variables. Columns (5) through (7) extend this by adding the output growth risk proxies to the baseline. This allows us to assess the additional explanatory power, measured by the increase in adjusted R^2 (incremental R^2), provided by each risk proxy.

Although the magnitudes of the risk proxy coefficients estimated from the multiple regressions are smaller than those observed in the univariate regression specifications, their statistical significance remains robust. Furthermore, the effects of the three risk proxies are economically meaningful. Notably, only the GaR coefficient in the AAA20Y spread regression is statistically significant at the 5% level. This supports the view that higher-credit-quality debt is less sensitive to macroeconomic tail risk than the BAA20Y credit spread.

Severe economic downturns can cause significant simultaneous declines in both consumption and cash flows, increasing the risk of widespread defaults. In such circumstances, marginal utilities rise as risk aversion and loss rates grow, leading to higher default premiums. The regression results shown in column (5) indicate that a one standard deviation (about 0.51) increase in GaR is associated with an approximate widening of the

AAA20Y spread by 5.1 basis points (calculated as ~ 0.51×0.1×100bps), while the BAA20Y credit spread increases by about 19.9 basis points (calculated as ~ 0.51 × 0.39 × 100 bps).[18] The heightened sensitivity of the BAA20Y credit spread supports concerns among scholars and professionals regarding the BAA-rated bond segment's vulnerability to defaults and downgrades during economic downturns or crises (see, for example, Acharya et al., 2025).

The regressions in column (6) utilise IP growth uncertainty (UNC) as a risk indicator. The results show that a one-standard-deviation increase in UNC (approximately 0.38) is associated with an increase of about 5.3 and 17.9 basis points in AAA20Y and BAA20Y credit spreads, respectively. This positive relationship between uncertainty and credit spreads supports previous research indicating that higher uncertainty negatively impacts financial markets (e.g., Kaviani et al., 2020). Elevated macroeconomic uncertainty can raise the likelihood of default (thereby widening credit spreads) by weakening corporate performance through lower consumption and slower economic growth, and by increasing financing costs, which hampers growth (Yang and Tan, 2010; Bloom, 2014).

Column (7) indicates that a one standard deviation increase in SKEW (around 0.05) reduces the AAA20Y (BAA20Y) credit spread by approximately eight basis points (14.8 basis points). An increase in SKEW suggests higher upside risks to economic growth, signalling a positive macroeconomic outlook aligned with strong corporate fundamentals. This scenario should boost bond valuations and lead to narrower credit spreads, which generally lowers corporate borrowing costs. Regression 8 includes both UNC and SKEW as explanatory variables. The results show that SKEW's coefficient is statistically significant for both credit spreads; however, UNC remains significant for the BAA20Y spread but is statistically insignificant for the AAA20Y spread.

The regression results in columns (5) to (8) indicate that the estimated coefficients and t-statistics for the BAA20Y spread regressions are generally two to three times higher than those for the AAA20Y spread regressions. Furthermore, the adjusted R^2 values for the BAA20Y spread regressions are roughly twice as large as those for the AAA20Y spread regressions. This shows that the explanatory variables have greater explanatory power for the segment of investment-grade debt with higher default risk.

The regression specification in column (1) includes only control variables as covariates and explains approximately 35% (64%) of the variation in AAA20Y and

[18] To gauge the impact, note that from Table 3.3, the standard deviation of the AAA20Y (BAA20Y) spread is 32 (59) bps.

BAA20Y credit spreads, respectively. The specifications in columns (5) to (7) show that adding GaR, UNC, and SKEW to the baseline specification individually increases the adjusted R^2 for the AAA20Y spread regression (Panel A) by 1.2%, 1.6%, and 3.9%, while raising the R^2 values for the BAA20Y credit spread regressions (Panel B) by 6.1%, 6.1%, and 4.1%, respectively.

The signs of the coefficient estimates for the control variables, as shown in Panels A and B, align with expectations. The IP growth coefficients are negative and statistically significant at the 1% level across all regression models for both credit spreads. Although the first moment of industrial production growth displays procyclical behaviour, credit spreads are fundamentally countercyclical, which explains the observed negative correlation.

The VXO index exhibits positive coefficients that are significant at the 1% level across all specifications of the BAA20Y spread regression. In contrast, its coefficients in the AAA20Y spread regression are significant only at the 5% level in regression specifications that include GaR or UNC risk measures, and at the 10% level in the regression that includes SKEW. An increase in the VXO index indicates rising market uncertainty, prompting investors to demand higher risk premiums, thereby increasing credit spreads (Campbell and Taksler, 2003). These findings imply that our output growth risk measures capture additional aspects of economic risk that are not reflected in the VXO.

The T-bill coefficients are negative and statistically significant in all specifications of the credit spread regression. This accords with Longstaff and Schwartz (1995), who show an inverse relationship between credit spreads and the risk-free rate. High interest rates are usually linked to an expanding economy and narrowing credit spreads (Huang and Kong, 2003). The Treasury slope coefficients are negative but statistically insignificant across all regressions for the two credit spreads, consistent with Collin-Dufresne et al. (2001).

The regression coefficients for the consumer sentiment indicator are negative for both spreads, consistent with Tang and Yan (2010). However, the relationship is statistically significant only in the BAA20Y spread regressions. Overall, the coefficients for stock returns are statistically insignificant across all models.

3.4.1.2 ***Long-term effects***

A pertinent question is whether these risk measures provide meaningful information about future corporate credit spreads. To examine the long-term effects of output growth risk, we conduct the following regression analysis:

$$CS_{i,t+h} = \alpha + \beta RP_{t-2} + \gamma_1 IPGrowth_{t-2} + \gamma_2 LogVXO_t + \gamma_3 Sentiment_t + \gamma_4 r_t + \gamma_5 Tbill_t + \gamma_6 TS_t + \varepsilon_{t+h}, \quad (3.10)$$

where $CS_{i,t+h}$ is the h-step-ahead credit spread, considering horizons up to 12 months ahead.

For brevity, the results in Table 3.5 for horizons up to 9 months ahead exclude the coefficient estimates for the control variables and the constant term. Panel A of Table 3.5 demonstrates that the effects of GaR and UNC on the AAA20Y credit spread are more transient than their effects on the BAA20Y spread. GaR has no statistically significant effect on the AAA20Y credit spread over the 12-month forecast horizon, whereas UNC's effect is statistically significant at the 5% level only in the t+1 month. Conversely, Panel B shows that GaR and UNC are highly significant at forecasting horizons up to four months ahead.

The significance of SKEW is relatively more persistent. Its negative effect on credit spreads remains statistically significant for up to six months for the AAA20Y spread and up to nine months for the BAA20Y spread. Furthermore, over the nine-month forecast period, the SKEW coefficients and adjusted R^2 values for the BAA20Y series are approximately twice those of the AAA20Y spread series.

3.4.2 Robustness checks

3.4.2.1 Evidence from the instrumental variable regressions

The OLS regressions based on equation (3.9) assume that the error term is independent of the regressors. Violations of the exogeneity assumption can lead to biased and inconsistent parameter estimates. Endogeneity of one or more explanatory variables may arise from omitted variables, measurement errors, or reverse causality between macroeconomic variables and credit spreads. A further concern is that the economic growth risk proxies are generated regressors, which can introduce a downward bias in standard errors (Pagan, 1984). Therefore, to assess the robustness of our OLS findings, we apply the instrumental-variable generalised method of moments (IV-GMM) method to our primary regression specification.

A common method to address potential endogeneity caused by reverse causation is to lag the explanatory variables. In the previous section, the OLS regressions lagged both output growth and the related risk proxies by two months. Since corporate bond credit spreads are inherently forward-looking, they are expected to reflect investors' expectations of future economic conditions in current prices. Therefore, it is impossible for forward-looking credit spreads to influence past macroeconomic indicators. However, endogeneity concerns may remain due to bidirectional causality between credit spreads and certain

independent variables. Furthermore, omitted-variable bias could be an issue, as shocks affecting credit spreads that are not fully captured may also impact some covariates.

Candidate instrumental variables should be correlated with the endogenous regressor but not directly influence the dependent variable. To evaluate the suitability of the instrumental variable approach, we conduct the Hausman test to assess the exogeneity of the regressors.[19] In this context, we assume that IP growth and the economic growth risk proxies are exogenous because they are lagged, whereas the remaining explanatory variables are endogenous.

We use lagged values of the 3-month Treasury bill, the Treasury slope, the consumer sentiment measure, and the VXO as instruments. The exogeneity of these instruments is justified by the assumption that the U.S. Treasury bond market operates efficiently and that current credit spreads reflect all past information. To instrument the stock return, we employ the overall Equity Market Volatility (EMV) tracker, including both its current and one-month-lagged values.

We use the Hansen J-statistic to evaluate whether the instruments are exogenous by testing the null hypothesis that they are uncorrelated with the error term. This test examines overidentifying restrictions, in which the joint null hypothesis posits that the instruments are valid and correctly excluded from the equation. When the null hypothesis is true, the test statistic follows an asymptotic chi-square distribution with degrees of freedom equal to the number of overidentifying restrictions.

The IV-GMM results in Table 3.6 closely resemble those from the OLS regression. The risk measure coefficient estimates demonstrate consistent qualitative patterns and similar levels of statistical significance. Notably, the GaR coefficient in the AAA20Y-spread regression is significant at the 10% level, supporting the OLS finding that the regressors have limited explanatory power for the AAA20Y spread. At the 5% significance level, we fail to reject the null hypothesis based on the Hansen J-statistic, confirming that the instruments are uncorrelated with the error terms and validating their use. Overall, these results reinforce the OLS conclusion that our variables play an important role in explaining credit spreads.

[19] The Hausman test approach is summarised in the appendix.

*3.4.2.2 **Further evidence from Option Adjusted Spreads***

Investment-grade debt generally carries lower to moderate credit risk than high-yield (speculative) debt. The high-yield segment is viewed as more sensitive to adverse economic conditions. Furthermore, many corporate bonds include an embedded call option that allows issuers to redeem them early. This feature can significantly affect the relationship between credit spreads and macroeconomic risk (Duffee, 1998).

We evaluate the robustness of our findings by analysing how business cycle risks affect high-yield (HY) and investment-grade (IG) Option-Adjusted Spreads (OAS). The OAS is an alternative measure of the yield spread between a corporate bond and a comparable Treasury security, adjusted for embedded options. This measure effectively reflects default risk, liquidity premiums, tax factors, and the bond's valuation status. The OAS data are obtained from FRED.

The OLS results presented in Table 3.7 show that the coefficients for the output growth risk measures are statistically significant at the 1% level. Importantly, the risk proxy coefficients in the HY-OAS regressions are approximately three to four times larger than those in the IG-OAS spread regressions, suggesting that high-yield debt is more sensitive to macroeconomic fluctuations. Specifically, a one-standard-deviation increase in GaR leads to an increase of about 113 bps in HY-OAS spreads, and 35 bps in IG-OAS spreads. Similarly, a one-standard-deviation increase in UNC significantly increases the HY-OAS and IG-OAS spreads by roughly 91 and 29 bps, respectively. Conversely, a one-standard-deviation increase in SKEW decreases the HY-OAS and IG-OAS spreads by approximately 67 and 16 bps, respectively.

Interestingly, the adjusted R^2 values indicate that the regressors account for nearly identical proportions of variation in the IG-OAS and HY-OAS spreads. Using regression (1) as a baseline, regressions (5) through (7) demonstrate that adding GaR, UNC, and SKEW individually improves the explanatory power of the IG-OAS (HY-OAS) spread regressions by approximately 9%, 8%, and 2% (10%, 9%, and 4%), respectively. Aside from the S&P 500 returns, all other explanatory variables are statistically significant at the 1% level in the IG-OAS spread regressions in Panel A of Table 3.7. The S&P 500 returns and Treasury slope variables are also insignificant across all HY-OAS spread regressions, consistent with the findings of Chan and Marsden (2014). Furthermore, the coefficients on sentiment and the 3-month T-bill rate in the HY-OAS regressions are statistically significant at the 5% level or below. The reduced sensitivity of high-yield bonds to interest rates aligns with the analysis

of Blume et al. (1991), who attribute this to embedded call options and elevated coupon rates.

3.4.2.3 Alternative approach to constructing risk proxies

We also evaluate the robustness of our baseline results by using Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models to construct the risk proxies. Brownlees and Souza (2021) demonstrate that GARCH models, widely employed for volatility forecasting, perform comparably to quantile regressions when predicting growth-at-risk. However, because the skewness metric, derived from the third central moment, is sensitive to outliers (Colacito et al., 2016), we use the GARCH methodology solely to construct the IP GaR and volatility (UNC) risk proxies.

The mean equation and GARCH model are specified using the Bayesian Information Criterion (BIC), which favours parsimony in model selection. The BIC recommends an ARMA(1,2) model for the conditional mean and a GJR-GARCH(1,1) process, assuming the error term follows a standard Student's t-distribution. This approach captures the non-Gaussian features of industrial production (IP) growth, as shown in Table 3.3.[20]

Panel A of Table 3.8 shows the parameter estimates for the ARMA-(GJR)GARCH model. Panel C shows that the correlations between the GARCH-based and QR-based GaR measures are 0.82 and 0.80 for the UNC measures, respectively. The high correlations reassure us that our quantile-based skewness measure is reliably estimated.

We re-run the OLS regression specifications in columns (5) and (6) of Table 3.4 and the GMM regressions in columns (1) and (2) of Table 3.5, using the GARCH-based GaR and UNC instead of their QR-based counterparts. Consistent with the baseline estimates, Table 3.9 shows a positive relationship between the two risk proxies (GaR and UNC) and investment-grade credit spreads.

The results also show that output growth risks have a relatively smaller influence on the AAA20Y spread. The GaR and UNC coefficients in the AAA20Y spread regressions are significant at the 5% level, while they are highly significant at the 1% level for the BAA20Y spread. The covariates' explanatory power, as indicated by the adjusted-R^2 values, is similar to that of the benchmark OLS regressions presented in Table 3.4.

[20] A description of the GARCH model can be found in the appendix.

3.4.3 Additional tests

3.4.3.1 Quantile regressions

OLS concentrates on the conditional mean of the dependent variable, summarising the central response to the explanatory factors. We also conduct a robustness check using QR regression to analyse how output growth risks affect credit spreads across quantiles. Existing research indicates that relationships among macroeconomic and financial series often involve non-linearities and asymmetries. Furthermore, these datasets frequently display skewness, fat tails, outliers, and heteroscedasticity, which can diminish the effectiveness of OLS regression. In contrast, QR enables examination of specific points in the conditional distribution of the dependent variable, providing insights that traditional OLS might overlook.

We perform quantile regression (QR) to estimate equation (3.9). The slopes of the regressors are estimated at the quantiles of 0.05, 0.25, 0.50, 0.75, and 0.95. QR estimation uses the pseudo R-squared as a goodness-of-fit measure, similar to the traditional R-squared in ordinary least squares (OLS) regression (see Koenker and Machado, 1999).[21]

The QR results are shown in Tables 3.10, 3.11, and 3.12. They closely match the OLS findings in several ways. For the analysed conditional quantiles, the regression coefficients for GaR (Panel A) and UNC (Panel B) in the BAA20Y spread regressions remain positive and statistically significant at the 1% level. The impact of downside tail risk and uncertainty in output growth on the BAA20Y spread is statistically significant not only at the median but also at the extremes of the spread distribution. This indicates that the link between the BAA20Y spread and the GaR and UNC measures remains consistent, regardless of whether credit risk is low or high.

Conversely, both GaR (shown in Panel A) and UNC (shown in Panel B) have no statistically significant impact on the AAA20Y spread at the 5th quantile. This emphasises the resilience of AAA-rated corporate debt during severe economic downturns and periods of heightened uncertainty, especially when credit risk remains low.

Panel C indicates that SKEW has substantial effects across the entire range of investment-grade credit spreads. The estimated SKEW coefficients are consistently negative

[21] QR analysis requires variables to be stationary to ensure accurate estimation and interpretation of the quantile slopes in the model. Unit root testing indicated that the covariates are stationary except for the 3-month Treasury bill series. We tested various specifications where the T-bill rate is either dropped, detrended, or differenced to achieve stationarity. Both restricted and unrestricted models produced consistent results. Since the T-bill rate is not our primary variable of interest, we used the raw T-bill series to estimate the QRs.

and statistically significant at the 1% level across the conditional quantiles of the AAA20Y and BAA20Y spreads. The exceptions are the 5th conditional quantile of the AAA20Y spread, where the SKEW coefficient is significant at the 5% level, and the 95th conditional quantile of the BAA20Y spread, where the SKEW coefficient is significant at the 10% level.

In absolute terms, the slope coefficients for all three risk proxies are higher at the 95th quantile compared to the 5th quantile. This indicates increased sensitivity of corporate spreads to output growth risks during periods of exceptionally high credit risk, compared with low-credit-risk regimes.

Consistent with the benchmark OLS results, the explanatory power of the empirical variables is higher for the BAA20Y spread, with pseudo-R^2 values ranging from approximately 38% to 61%. In contrast, it is lower for the AAA20Y specifications, ranging from 19% to 31%.

The results for the control variables align with theoretical expectations. The VXO and the 3-month T-bill rate are the most significant factors explaining the BAA20Y credit spread, demonstrating strong, significant relationships at the 1% level across the spread's conditional distribution. A similar pattern appears in the regressions for the AAA20Y spread; however, the statistical significance of the VXO and T-bill rate coefficients is somewhat reduced at higher conditional quantiles.

In addition to confirming the main OLS regression results, several other important observations emerge. The consumer sentiment variable has a statistically significant negative effect on the AAA20Y spread at lower quantiles but a statistically significant positive effect at higher quantiles. The estimated effect of consumer sentiment is negative and statistically significant across all quantiles of the BAA20Y spread. The Treasury slope significantly influences spreads at the lower quantiles, mainly narrowing them during normal periods or when credit risk in the economy is low. The negative coefficients of the IP growth factor are mostly statistically significant for the 50th and 75th quantiles of the AAA20Y spread distribution. In the case of the BAA20Y spread, the 95th conditional quantile coefficient of IP growth is generally insignificant.

3.4.3.2 Principal component analysis

Panel B of Table 3.3 indicates that GaR, UNC, and SKEW are strongly correlated, potentially leading to multicollinearity issues if all three are included in regression models. To address this, one approach is to perform principal component analysis (PCA) on these three lagged risk measures and then use the resulting principal components as regressors.

PCA is a dimension-reduction technique that transforms a set of original variables into fewer composite factors while minimising information loss. It relies on the eigen-decomposition of the covariance or correlation matrix. The resulting principal components are orthogonal combinations of the variables and capture most of the variance, with each representing independent information. For instance, the first principal component explains the greatest amount of variability (variance) in the data. Each subsequent component explains the maximum remaining variance that is uncorrelated with previous components. The extracted principal components help stabilise coefficient estimates and reduce the influence of noise in regressions. A detailed explanation of this method can be found in Appendix 3.7.5.

We use the Ahn and Horenstein (2013) method to determine the maximum number of factors. The Eigenvalue Ratio and Growth Ratio estimators from Ahn and Horenstein (2013) suggest retaining the first principal component. A scree plot in Figure 3.3 displays the eigenvalues of the covariance matrix, ordered from highest to lowest. The Kaiser criterion (Kaiser, 1960) recommends keeping the first principal component because it is the only one with an eigenvalue greater than 1.0. The rationale is that each standardised variable contributes one unit of variance to the dataset's total variance. Therefore, any component with an eigenvalue above 1.00 captures a significant amount of variance and should be retained.

The orthonormal loadings map in Fig. 3.4 shows that the first principal component explains approximately 81.7% of the total variation, while the second principal component accounts for 15.7%. Interestingly, the first principal component correlates more strongly with GaR and UNC risk measures, whereas the second principal component correlates more strongly with SKEW. These criteria suggest that the first principal component, which we refer to as *MacroRisk*, is the most influential factor, so we retain it. Figure 3.5 plots the first principal component derived from the three risk proxies. The factor is positive and peaks during recessions and periods of financial turmoil.

In this section, we estimate the following linear regression model for each credit spread:

$$CS_t = \alpha + \beta MacroRisk_t + \gamma_1 IPGrowth_{t-2} + \gamma_2 LogVXO_t + \gamma_3 Sentiment_t + \gamma_4 r_t + \gamma_5 Tbill_t + \gamma_6 TS_t + \varepsilon_t, \quad (3.11)$$

where $MacroRisk_t$ is the first principal component derived from GaR_{t-2}, UNC_{t-2}, and $SKEW_{t-2}$. The results in Table 3.13 show that the retained principal component is

significantly positively related to both credit spreads, confirming the impact of macroeconomic risk.

Panel A of Table 3.13 shows that a one-standard-deviation increase in $MacroRisk$ (about 1.57) is associated with a widening of the AAA20Y spread by approximately 8bps, while the BAA20Y credit spread increases by approximately 22bps. We also present results from regressions using the investment-grade and high-yield OAS in Panel B. A one-standard-deviation increase in the principal component is associated with an almost 33 bps increase in the IG-OAS spread, while the HY-OAS spread increases by approximately 111 bps.

Compared to the adjusted-R^2 for the OLS baseline specification reported in column (1) of Table 3.4, the extracted principal component improves the explanation of both credit spreads when added to the benchmark regression model. The additional explanatory power is nearly 7.5% for the BAA20Y regression, exceeding that of regression specifications (5) to (8) shown in Table 3.4. The extra contribution to explaining the AAA20Y spread is around 3%, slightly higher than that from regression specifications that include GaR and UNC risk measures but lower than that achieved with the SKEW specification. Furthermore, the variance in credit spreads explained by the univariate regressions with the principal component exceeds that accounted for by each of the individual risk measures shown in Table 3.4.

3.4.4 Discussion and Implications

Our findings show that corporate credit spreads widen considerably during times of increased macroeconomic risk, especially when economic growth becomes more uncertain, and the distribution becomes negatively skewed due to heightened downside risks. We demonstrate that the BAA-rated segment of the investment-grade category is particularly vulnerable under such challenging conditions.

Our work has important implications for the credit risk assessment literature. Our results suggest that Merton's (1974) structural model of default can be enriched by incorporating measures of adverse economic states, namely tail risk and higher-moment risk in economic output. This improvement potentially can aid in resolving the credit spread puzzle.

These results also have significant economic implications. Credit spreads tend to widen after an extreme negative economic shock as investors usually require much higher

premiums, leading to increased borrowing costs. Rising refinancing costs result in notably higher debt service expenses, which can weaken firm fundamentals. Under tighter credit conditions, some firms may lose access to public debt markets (Acharya and Steffen, 2020). As the credit outlook worsens, many BAA-rated companies are likely to be downgraded to high-yield status, thus becoming fallen angels. The financial system and the real economy are connected through the corporate bond market, which finances real activities that drive economic growth. A malfunction or disruption in debt markets can reduce consumption and investment and, through the financial accelerator mechanism (Bernanke et al., 1999), amplify the propagation of shocks that weaken aggregate economic activity, thereby exacerbating output losses.

Our results thus inform policymakers pursuing a "plan for the worst, hope for the best" approach to reduce business-cycle costs from adverse shocks. Policymakers must accurately assess macroeconomic tail risks and their implications to enhance preparedness for economic crises and enable pre-emptive action to limit vulnerabilities. According to Bernanke (2018), economists and policymakers relying on standard macroeconomic models, which use indicators such as GDP growth or inflation, significantly underestimated the ultimate impact of the GFC on the real economy. A low perceived risk of an economic crisis can lead to asset overvaluation, resulting in excessive leverage build-up during credit booms and making the economy increasingly vulnerable to negative shocks, as witnessed in the 2008-2009 financial crisis. Furthermore, failing to account for economic risk and its implications could lead to regulatory reforms that have detrimental consequences for investors and the economy.

Deteriorating macroeconomic conditions can greatly impact financial stability. Increasing debt levels and declining creditworthiness raise concerns about how well potential risks during an economic downturn are understood. Poor economic prospects, characterised by low growth and high uncertainty, increase the chances of a surge in downgrades and defaults. Investment-grade bonds rated BBB are mainly held by institutional investors such as insurers, pension funds, and banks (Koijen and Yogo, 2023). Falling asset values weaken their balance sheets, reducing their ability to provide insurance, extend credit, and participate in capital markets. Investors subject to regulatory restrictions (such as insurance companies) or self-imposed investment policies will divest from fallen angels (Boyarchenko and Shachar, 2020). At the same time, negative risk sentiment triggers fire sales, lowering bond prices and widening credit spreads, which further intensifies market stress and raises concerns about financial stability.

Our research offers crucial insights for regulators seeking to develop measures to support credit supply during periods of declining economic conditions and weakening credit quality, thereby helping to prevent credit market disruptions. Our findings can assist financial institutions and regulators in fine-tuning risk models to forecast and prepare for crises, as well as in designing stress tests. Additionally, our research can support the development of early-warning systems for future economic and financial crises.

Policy initiatives that help firms build cash reserves can establish financial buffers against economic downturns, reducing the risk of default and preventing increases in credit spreads. Holding financial assets that exceed total liabilities, particularly interest-bearing assets, provides resources to withstand the adverse effects of higher interest rates driven by widening credit spreads (Albuquerque et al., 2025). Policymakers have responded to recent episodes of stress (e.g., the COVID-19 pandemic) by establishing credit and liquidity facilities to mitigate systemic risks as investors sell riskier assets and U.S. investment-grade corporate bond issuance declines (Boyarchenko et al., 2025).

3.5 Conclusion

Policymakers and scholars have expressed concerns about the increasing indebtedness of the U.S. investment-grade bond market amid heightened vulnerabilities in a difficult macroeconomic environment. They are concerned that a potential adverse macroeconomic scenario could lead to a surge in downgrades or defaults, threatening economic activity and financial stability.

This chapter explores whether macroeconomic risk—measured by the probability of extreme growth outcomes (GaR), uncertainty (UNC), and the skewness of the growth distribution (SKEW)—influences U.S. investment-grade corporate credit spreads. These factors are considered the risks that agents might genuinely be concerned about. As Timmermann (2000) explains, decision-makers with an asymmetric loss function that depends on future variable values need complete knowledge of the variable's conditional density, not just its conditional mean and variance.

We utilise the growth rate of U.S. industrial production and apply quantile regression to develop our risk measures. The estimated, time-varying economic growth risk measures are correlated with the uncertainty measures of Ludvigson et al. (2021) and the skewness measure proposed by Iseringhausen et al. (2023).

We observe that credit spreads tend to widen when GaR and UNC increase, and they narrow when skewness is positive. Our analysis shows that the coefficients of the three risk proxies are highly statistically significant in the regression models and enhance their explanatory power. Notably, the BAA20Y credit spread is more sensitive to output growth risks than the AAA20Y spread. Furthermore, the explanatory power of the regression models for the BAA20Y spread increases substantially, while the gain is modest for the AAA20Y spread. Our findings also indicate that SKEW is more persistent and provides valuable information for BAA20YR (AAA20YR) spreads over a 9-month (6-month) forecast period. Meanwhile, the effects of GaR and UNC are largely confined to the BAA20YR spread over a 4-month horizon.

These empirical findings are robust across alternative model specifications, including: (i) a Generalised Method of Moments (GMM) framework with instrumental variables to address potential endogeneity; (ii) a quantile regression framework; (iii) the GARCH approach to derive GaR and UNC risk measures; and (iv) investment-grade and high-yield option-adjusted spreads (OAS) as dependent variables. These robustness tests yield results consistent with the benchmark ordinary least squares (OLS) regressions. OAS regressions strengthen our benchmark results, demonstrating that high-yield spreads are more sensitive to macroeconomic risks than investment-grade spreads. Additionally, a principal component is extracted from GaR, UNC, and SKEW, and credit spreads are regressed against this component. The findings indicate that the principal component can explain credit spreads, with its additional explanatory power surpassing that of any of the three risk measures.

Policymakers must remain vigilant in monitoring the evolving size, quality, and dynamics of the investment-grade corporate bond market. The increased indebtedness, coupled with lower overall credit quality, heightens the potential negative impact of an economic downturn on this sector and the wider economy (Çelik et al., 2020).

Ignoring tail risk and higher moments in policy and investment decisions can contribute to a build-up of risk, leaving agents poorly prepared for an economic crisis. A good understanding of how corporate credit spreads respond to macroeconomic risks helps policymakers develop strategies to reduce corporate vulnerability to negative economic shocks. As previously noted, an increase in downgrades and defaults could limit lending and create a vicious cycle of tighter funding conditions and reduced access to finance for some firms. Such a disruption in the bond market reduces firms' investment, with negative implications for financial stability and the real economy.

The findings of this chapter are vital for practitioners and policymakers. Understanding how macroeconomic risk impacts corporate credit risk is essential for effective risk management, trading, and monetary policy decisions, ultimately boosting investor confidence and strengthening bond market resilience during economic crises.

The relationship between credit spreads and macroeconomic risks may vary across different economic regimes. It is suggested that declining investor sentiment enhances the sensitivity of credit markets to macroeconomic risks. Therefore, future research could consider using regime-shifting models.

3.6 Figures and tables

3.6.1 Tables

Table 3.1 Data description and sources

Variable name	Frequency	Source
Moody's Seasoned Baa Corporate Bond Yield, Percent, Not Seasonally Adjusted	Monthly	Federal Reserve Economic Data
Moody's Seasoned Aaa Corporate Bond Yield, Percent, Not Seasonally Adjusted	Monthly	Federal Reserve Economic Data
US Treasury Yield Adjusted to Constant Maturity - 20 Year, Not Seasonally Adjusted	Monthly	DataStream
ICE BofA US Corporate Index Option-Adjusted Spread, Percent, Not Seasonally Adjusted	Monthly	Federal Reserve Economic Data
ICE BofA US High Yield Index Option-Adjusted Spread, Percent, Not Seasonally Adjusted	Monthly	Federal Reserve Economic Data
CBOE S&P 100 Volatility Index: VXO, Index, Not Seasonally Adjusted	Monthly	Federal Reserve Economic Data
3-Month Treasury Bill Secondary Market Rate, Discount Basis, Percent, Not Seasonally Adjusted	Monthly	Federal Reserve Economic Data
University of Michigan: Consumer Sentiment, Index 1966:Q1=100, Not Seasonally Adjusted	Monthly	Federal Reserve Economic Data
SP500 Composite	Daily	DataStream
US Equity Market Volatility Index	Daily	https://www.policyuncertainty.com/EMV_monthly.html
Industrial Production: Total Index, Continuously Compounded Rate of Change, Seasonally Adjusted	Monthly	Federal Reserve Economic Data
Unemployment Rate, Percent, Seasonally Adjusted	Monthly	Federal Reserve Economic Data
Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Percent, Not Seasonally Adjusted	Monthly	Federal Reserve Economic Data
Chicago Fed National Activity Index	Monthly	Federal Reserve Economic Data
Chicago Fed National Financial Conditions Index, Index, Not Seasonally Adjusted	Monthly	Federal Reserve Economic Data
10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity, Not Seasonally Adjusted	Monthly	Federal Reserve Economic Data
Aruoba-Diebold-Scotti Business Conditions Index	Daily	https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads

***Notes*:** We use the monthly average of the SP500 Composite and the US Equity Market Volatility Index, based on daily data. We employ the monthly sum of the Aruoba-Diebold-Scotti Business Conditions Index and also the monthly sum of the Chicago Fed National Financial Conditions Index. All Data retrieved February 2024.

Table 3.2 Accuracy of the conditional quantiles

T	Actual Exceedances	UC	CC
5	20 (19)	0.889	0.990
50	194 (194)	1.000	0.390
95	367 (368)	0.713	0.069

Notes: This table reports the backtest results. The numbers in parentheses are the expected exceedances. The p-values of the unconditional coverage test (UC) of Kupiec (1995) and the conditional coverage (CC) test of Christoffersen (1998) are reported. The null hypothesis of the UC is that the proportion of exceedances equals the quantile (i.e., non-rejection of the null is preferred). The null hypothesis of the CC is that the failure process is independent and that the expected proportion of violations equals the quantile.

Table 3.3 Summary statistics

Panel A: Descriptive statistics

	Mean	Median	Max	Min	Std. Dev.	Skew	Kurt	AR(1)	ADF
Spreads									
BAA20Y	0.94	0.93	1.87	0.44	0.32	0.41	2.48	0.95	-3.92***
AAA20Y	1.90	1.85	5.25	1.08	0.59	2.02	10.91	0.96	-4.10***
Risk measures									
GaR	-0.60	-0.53	0.37	-3.38	0.51	-2.02	10.09	0.88	-4.55***
UNC	1.48	1.42	3.83	0.63	0.38	2.02	11.27	0.71	-5.01***
SKEW	0.02	0.02	0.16	-0.20	0.05	-0.63	5.43	0.49	-6.41***
Controls									
IP growth	0.14	0.19	2.04	-4.48	0.62	-1.66	12.59	0.22	-5.50***
VXO	2.91	2.87	4.18	2.08	0.37	0.52	3.12	0.90	-4.40***
Consumer Sentiment	4.47	4.51	4.72	4.01	0.14	-0.88	3.44	0.94	-3.28**
Stock returns	0.01	0.01	0.11	-0.23	0.04	-1.38	9.25	0.25	-15.22***
3-month Treasury yield	3.04	2.95	8.82	0.01	2.45	0.30	1.94	0.995	-1.76
Treasury slope	1.71	1.69	3.71	-0.67	1.14	-0.10	1.91	0.98	-2.97**

Panel B: Correlations

BAA20Y	1.00									
AAA20Y	0.82	1.00								
GaR	0.47	0.71	1.00							
UNC	0.44	0.65	0.91	1.00						
SKEW	-0.51	-0.62	-0.67	-0.58	1.00					
IP growth	-0.35	-0.46	-0.55	-0.41	0.33	1.00				
VXO	0.33	0.52	0.38	0.30	-0.43	-0.15	1.00			
Consumer Sentiment	-0.28	-0.53	-0.48	-0.45	0.47	0.22	-0.21	1.00		
Stock returns	-0.20	-0.23	-0.17	-0.15	0.15	-0.01	-0.40	0.15	1.00	
3-month Treasury yield	-0.41	-0.42	-0.16	-0.19	0.15	0.11	0.10	0.39	0.02	1.00
Treasury slope	0.16	0.25	0.02	0.06	-0.08	0.05	0.10	-0.48	-0.09	-0.52

Notes: Panel A presents descriptive statistics. GaR, UNC and SKEW denote growth-at-risk, uncertainty and skewness, respectively. ADF denotes the Augmented Dickey-Fuller test with the null hypothesis that the series has a unit root I(1). *, **, and *** denote the significant level at 1%, 5%, and 10% level, respectively. The VXO and the Consumer Sentiment Index in log terms. Panel B presents the correlations between the variables. The sample period covers between August 1987 and December 2019.

Table 3.4 OLS regression estimates

Regressions	1	2	3	4	5	6	7	8
Panel A	**Dependent variable: AAA20Y**							
GaR		0.26***			0.10**			
		[4.42]			[2.12]			
UNC			0.33***			0.14***		0.06
			[4.76]			[2.92]		[1.29]
SKEW				-2.83***			-1.60***	-1.40***
				[-5.50]			[-5.10]	[-4.23]
IP growth	-0.10***				-0.06***	-0.08***	-0.07***	-0.07***
	[-4.18]				[-3.72]	[-4.20]	[-3.43]	[-3.37]
log VXO	0.29**				0.25**	0.26**	0.23*	0.22*
	[2.39]				[2.14]	[2.22]	[1.93]	[1.89]
Sentiment	-0.09				0.03	0.02	0.1	0.13
	[-0.27]				[0.09]	[0.06]	[0.32]	[0.40]
Stock return	-0.54				-0.4	-0.38	-0.59	-0.61*
	[-0.62]				[-0.96]	[-0.97]	[-1.59]	[-1.66]
3-month Treasury yield	-0.06***				-0.06***	-0.06***	-0.06***	-0.06***
	[-3.06]				[-3.10]	[-3.11]	[-3.16]	[-3.19]
Treasury slope	-0.04				-0.04	-0.04	-0.033	-0.03
	[-0.75]				[-0.64]	[-0.67]	[-0.62]	[-0.55]
Intercept	0.76	0.78***	0.45***	1.00***	0.26	-0.15	-0.11	-0.1
	[0.48]	[9.97]	[3.56]	[18.79]	[0.16]	[-0.09]	[-0.07]	[-0.06]
Adjusted-R^2	35.45%	16.50%	15.02%	18.29%	36.66%	37.04%	39.35%	39.52%
Panel B	**Dependent variable: BAA20Y**							
GaR		0.783***			0.39***			
		[5.04]			[4.27]			
UNC			0.979***			0.47***		0.37***
			[4.42]			[4.61]		[3.20]
SKEW				-7.095***			-2.95***	-1.80***
				[-3.76]			[-5.94]	[-4.37]
IP growth	-0.25***				-0.12***	-0.17***	-0.21***	-0.16***
	[-5.35]				[-4.42]	[-6.41]	[-5.13]	[-6.22]
log VXO	0.77***				0.63***	0.66***	0.65***	0.61***
	[4.63]				[4.96]	[5.28]	[4.35]	[5.03]
Sentiment	-1.09***				-0.63*	-0.72**	-0.74**	-0.58*
	[-2.59]				[-1.74]	[-2.10]	[-2.10]	[-1.79]
Stock return	0.81				0.22	0.36	0.19	0.07
	[1.19]				[0.37]	[0.66]	[0.31]	[0.14]
3-month Treasury yield	-0.10***				-0.09***	-0.09***	-0.09***	-0.08***
	[-3.91]				[-3.69]	[-3.80]	[-4.20]	[-3.94]
Treasury slope	-0.07				-0.05	-0.06	-0.06	-0.05
	[-1.40]				[-0.91]	[-1.09]	[-1.24]	[-1.02]
Intercept	4.99***	1.427***	0.448	2.040***	3.02*	2.87**	3.79**	2.55
	[2.59]	[12.48]	[1.40]	[22.64]	[1.73]	[1.72]	[2.37]	[1.60]
Adjusted-R^2	63.86%	46.16%	40.07%	34.58%	69.99%	70.00%	67.92%	71.25%

Notes: The table reports the OLS coefficients and t-statistics (in parentheses) for each regression model. GaR, UNC and SKEW denote growth-at-risk, uncertainty and skewness, respectively. We estimate the standard errors via a HAC Newey-West procedure. We use a Bartlett kernel and Andrews' automatic optimal bandwidth. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1987M8–2019M12. Results from EViews version 12.

Table 3.5 The long-term effects of the output growth proxies

Horizon	*h*=1	*h*=2	*h*=3	*h*=4	*h*=5	*h*=6	*h*=7	*h*=8	*h*=9
Panel A	Dependent Variable: Aaa-Treasury								
GaR	0.06	0.05	0.06	0.04	0.02	0.00	-0.01	-0.02	-0.01
	[1.47]	[1.27]	[1.28]	[0.79]	[0.41]	[0.02]	[-0.12]	[-0.34]	[-0.24]
Adj-R²	34.3%	29.4%	24.0%	20.9%	19.2%	16.2%	14.1%	13.1%	12.0%
UNC	0.10**	0.07	0.08*	0.07	0.05	0.03	0.02	-0.01	-0.01
	[2.09]	[1.51]	[1.77]	[1.38]	[0.95]	[0.47]	[0.29]	[-0.13]	[-0.11]
Adj-R²	34.7%	29.5%	24.2%	21.1%	19.3%	16.3%	14.1%	13.0%	11.9%
SKEW	-1.36***	-1.30***	-1.05***	-0.93**	-0.97**	-0.79**	-0.69*	-0.59	-0.33
	[-4.12]	[-3.57]	[-2.68]	[-2.39]	[-2.57]	[-2.16]	[-1.88]	[-1.54]	[-0.84]
Adj-R²	36.7%	31.7%	25.3%	22.1%	20.6%	17.2%	14.9%	13.6%	12.1%
Panel B	Dependent Variable: Baa-Treasury								
GaR	0.29***	0.24***	0.22***	0.18**	0.14	0.10	0.09	0.06	0.05
	[4.20]	[3.54]	[2.87]	[2.09]	[1.44]	[0.91]	[0.75]	[0.52]	[0.44]
Adj-R²	67.7%	60.9%	52.8%	46.9%	42.1%	35.6%	30.2%	26.9%	25.0%
UNC	0.37***	0.28***	0.27***	0.23**	0.19*	0.12	0.09	0.05	0.03
	[4.56]	3.75	[3.07]	[2.40]	[1.84]	[1.01]	[0.70]	[0.31]	[0.17]
Adj-R²	68.0%	60.8%	52.8%	47.2%	42.4%	35.7%	30.2%	26.8%	24.9%
SKEW	-2.61***	-2.38***	-1.99***	-1.63***	-1.60***	-1.50***	-1.37**	-1.25**	-0.99*
	[-5.68]	[-4.70]	[-3.94]	[-3.64]	[-3.38]	[-3.09]	[-2.57]	[-2.18]	[-1.7]
Adj-R²	67.4%	61.3%	52.6%	46.9%	42.6%	36.3%	30.8%	27.5%	25.3%

Notes: This table presents the results of predictability regressions for corporate credit spreads using output growth risk proxies. The Newey–West t-statistics using a Bartlett kernel and Newey-West automatic optimal bandwidth are reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1987M8–2019M12. Results from EViews version 12.

Table 3.6 GMM regressions

Dependent Variable:	**AAA20Y**			**BAA20Y**		
	1	**2**	**3**	**1**	**2**	**3**
Risk measures						
GaR	0.09*			0.37***		
	[1.90]			[4.40]		
UNC		0.13***			0.45***	
		[2.66]			[4.81]	
SKEW			-1.47***			-2.53***
			[-4.39]			[-4.69]
Control Variables						
IP growth	-0.07***	-0.08***	-0.08***	-0.15***	-0.17***	-0.23***
	[-3.70]	[-3.76]	[-3.09]	[-4.26]	[-6.54]	[-5.80]
log VXO	0.29***	0.29**	0.27**	0.73*	0.76***	0.77***
	[2.41]	[2.50]	[2.10]	[5.22]	[7.00]	[5.63]
Sentiment	0.01	0.06	0.08	-0.63*	-0.66**	-0.81**
	[0.03]	[0.20]	[0.26]	[-1.68]	[-2.36]	[-2.51]
Stock return	0.49	0.51	0.31	2.83**	0.72	3.36**
	[0.59]	[0.61]	[0.34]	[2.26]	[1.11]	[2.48]
Tbill	-0.06***	-0.06***	-0.06***	-0.09***	-0.09***	-0.09***
	[-2.89]	[-2.89]	[-2.91]	[-3.59]	[-5.54]	[-5.73]
Treasury slope	-0.03	-0.03	-0.03	-0.03	-0.05	-0.06
	[-0.61]	[-0.63]	[-0.58]	[-0.60]	[-1.16]	[-1.52]
Intercept	0.22	0.1	0.08	2.71	2.33*	3.72***
	[0.14]	[0.07]	[0.05]	[1.49]	[1.73]	[2.62]
Adjusted-R^2	36.0%	36.5%	38.5%	67.9%	69.7%	65.0%
J-statistic (Probability)	49.8%	86.3%	54.0%	63.9%	11.2%	83.8%

***Notes*:** GaR, UNC and SKEW denote growth-at-risk, uncertainty and skewness, respectively. The instrumental variables for the Aaa-Treasury spread include the current value of the EMV and one-month lags of the EMV, VXO and the 3-month T-bill. The instrumental variables for the Baa-Treasury spread when (i) using the GaR measure include the current value of the EMV and one-month lags of the EMV, VXO and the Treasury slope, (ii) using the SKEW measure include the current value and one-month lag of the EMV, and the one-month lag of VXO, and (iii) using the UNC measure include one and two-month lags of the VXO and the one-month lag of the Treasury slope. We use the two-stage least squares weighting matrix. The Newey–West t-statistics using a Bartlett kernel and Andrew's automatic optimal bandwidth are reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1987M8–2019M12. Results from EViews version 12.

Table 3.7 OLS regression estimates - Option adjusted spreads (OAS)

Panel: A	**Dependent Variable: IG-OAS**							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
GaR		1.28***			0.68***			
		[4.70]			[5.07]			
UNC			1.56***			0.75***		0.71***
			[3.94]			[4.91]		[4.51]
SKEW				-11.35***			-3.11***	-0.80*
				[-2.98]			[-3.84]	[-1.83]
IP growth	-0.32***				-0.08**	-0.18***	-0.27***	-0.17***
	[-3.93]				[-2.43]	[-4.50]	[-3.63]	[-4.44]
log VXO	1.19***				0.95***	0.99***	1.04***	0.96***
	{4.29]				[6.55]	[6.53]	[4.27]	[6.17]
Sentiment	-2.41***				-1.72***	-1.96***	-2.15***	-1.91***
	[-4.15]				[-5.95]	[-5.76]	[-4.25]	[-5.73]
Stock return	1.38				0.36	0.68	0.8700	0.5800
	[1.09]				[0.38]	[0.74]	[0.75]	[0.64]
Tbill	-0.14***				-0.12***	-0.11***	-0.11***	-0.101***
	[-3.79]				[-3.79]	[-3.50]	[-3.47]	[-3.19]
Treasury slope	-0.16***				-0.14***	-0.14***	-0.12**	-0.13**
	[-2.61]				[-2.70]	[-2.70]	[-2.31]	[-2.45]
Intercept	9.41***	0.72***	-0.81	1.76***	6.48***	6.71***	8.61***	6.63***
	[4.15]	[4.10]	[-1.48]	[10.52]	[4.83]	[4.57]	[4.30]	[4.56]
Adjusted-R^2	74.27%	58.81%	50.10%	39.16%	83.27%	82.00%	76.04%	82.04%
Panel: B	**Dependent Variable: HY-OAS**							
GaR		3.85***			2.22***			
		[7.37]			[8.47]			
UNC			4.67***			2.39***		2.10***
			[5.31]			[7.44]		[5.60]
SKEW				-35.22***			-13.34***	-6.54***
				[-3.80]			[-5.48]	[-3.40]
IP growth	-0.96***				-0.19**	-0.52***	-0.75***	-0.47***
	[-5.38]				[-2.01]	[-6.18]	[-5.20]	[-5.87]
log VXO	4.68***				3.90***	4.04***	4.03***	3.80***
	[5.86]				[8.77]	[8.50]	[5.93]	[8.46]
Sentiment	-3.74**				-1.48	-2.27**	-2.61*	-1.90*
	[-2.29]				[-1.36]	[-2.04]	[-1.86]	[-1.69]
Stock return	5.49				2.17	3.27	3.3400	2.4900
	[1.56]				[0.97]	[1.46]	[1.09]	[1.19]
Tbill	-0.38**				-0.32**	-0.28**	-0.25*	-0.23*
	[-2.34]				[-2.41]	[-2.13]	[-1.83]	[-1.83]
Treasury slope	-0.15				-0.07	-0.06	0.0200	0.0100
	[-0.59]				[-0.35]	[-0.31]	[0.10]	[0.05]
Intercept	9.57	3.04***	-1.52	6.19***	0.03	0.93	6.1400	0.3000
	[1.32]	[6.56]	[-1.19]	[14.46]	[0.01]	[0.16]	[0.98]	[0.05]
Adjusted-R^2	75.10%	57.24%	48.45%	40.88%	85.46%	83.66%	78.73%	84.37%

***Notes*:** The table reports the OLS coefficients and t-statistics (in parentheses) for each regression model. IG-OAS and HY-OAS denote investment-grade and high-yield OAS, respectively. GaR, UNC and SKEW denote growth-at-risk, uncertainty and skewness, respectively. We estimate the standard errors via a HAC Newey-West procedure. We use a Bartlett kernel and Andrews' automatic optimal bandwidth. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1997M1–2019M12. Results from Eviews version 12.

Table 3.8 ARMA-GJR-GARCH model

Panel A: GJR-GARCH estimation

Variable	Coefficient	z-Statistic
Mean equation		
Constant	0.14***	(2.75)
AR(1)	0.79***	(11.63)
MA(1)	-0.80***	(-9.40)
MA(2)	0.21***	(5.28)
Variance equation		
Constant	0.05***	(3.55)
Alpha	-0.09***	(-3.65)
Gamma	0.35***	(3.99)
Beta	0.73***	(10.65)
T-DIST. DOF	11.19**	(2.41)
Log likelihood	-275.8	
Durbin-Watson	1.84	

Panel B: Descriptive statistics

	Mean	Std. Dev	Skewness	Kurtosis	Jarque-Bera
GARCH UNC	0.52	0.21	4.94	33.27	16396.7***
GARCH GaR	-0.65	0.51	-3.82	22.51	7099.4***

Panel C: Risk proxy correlations

	UNC (GARCH)	GaR (GARCH)	QR UNC	QR GaR	QR SKEW
UNC (GARCH)	1.00	-0.96	0.80	-0.78	-0.45
GaR (GARCH)	-0.96	1.00	-0.79	0.82	0.45

Notes: z-statistics are given in parentheses. ARCH = Autoregressive Conditional Heteroscedasticity; AR = Autoregression; and MA = Moving Average. T-DIST DOF = t-distribution degrees of freedom. GaR = growth-at-risk. UNC=uncertainty. *p < 0.05, **p < 0.01, ***p < 0.001. Results from Eviews version 12.

This table reports the results of the estimated GJR-GARCH model, along with summary statistics for IP growth volatility (uncertainty) and growth-at-risk. Also presented are the correlations between the GARCH and QR-based risk measures.

Table 3.9 GARCH-based Growth-at-Risk and Uncertainty measures

Dependent Variable:	***AAA20Y***			
	OLS	***IV-GMM***	***OLS***	***IV-GMM***
GaR	0.08**	0.07*		
	[2.20]	[1.95]		
UNC			0.14**	0.12**
			[2.56]	[2.29]
IP growth	-0.08***	-0.09***	-0.09***	-0.10***
	[-4.41]	[-3.84]	[-4.26]	[-3.74]
log VXO	0.27**	0.31**	0.27**	0.31**
	[2.19]	[2.45]	[2.18]	[2.44]
Sentiment	-0.02	-0.04	-0.03	-0.05
	[-0.06]	[-0.12]	[-0.08]	[-0.14]
Stock return	-0.42	0.46	-0.39	0.52
	[-0.99]	[0.55]	[-0.93]	[0.61]
3-month Treasury Yield	-0.06***	-0.06***	-0.06***	-0.06***
	[-3.10]	[-2.87]	[-3.03]	[-2.81]
Treasury slope	-0.04	-0.04	-0.04	-0.04
	[-0.70]	[-0.66]	[-0.71]	[-0.67]
Constant	0.46	0.41	0.47	0.43
	[0.29]	[0.27]	[0.30]	[0.28]
Adjusted-R^2	36.3%	35.6%	36.0%	35.2%
Probability (J-statistic)		49.4%		52.3%
Dependent Variable:	***BAA20Y***			
GaR	0.39***	0.36***		
	[7.96]	[6.63]		
UNC			0.93***	0.89***
			[11.22]	[11.45]
IP growth	-0.16***	-0.19***	-0.19***	-0.18***
	[-6.69]	[-5.04]	[-7.11]	[-6.79]
log VXO	0.65***	0.73***	0.64***	0.73***
	[5.41]	[5.59]	[5.22]	[6.02]
Sentiment	-0.74**	-0.71**	-0.71**	-0.66*
	[-2.18]	[-2.01]	[-1.98]	[-1.78]
Stock return	-0.07	3.06***	-0.07	0.27
	[-0.10]	[3.06]	[-0.10]	[0.38]
3-month Treasury Yield	-0.08***	-0.08***	-0.09***	-0.09***
	[-3.79]	[-3.78]	[-3.64]	[-3.54]
Treasury slope	-0.06	-0.04	-0.06	-0.05
	[-1.07]	[-0.79]	[-1.10]	[-0.97]
Constant	3.43**	3.04*	3.10*	2.66
	[2.08]	[1.75]	[1.80]	[1.49]
Adjusted-R^2	72.4%	69.4%	72.7%	72.4%
Probability (J-statistic)		38.2%		25.1%

Notes: The table presents results from OLS and instrumental-variable GMM regressions of monthly corporate credit spreads on IP growth-at-risk, IP growth volatility, and controls. GaR and UNC denote growth-at-risk and uncertainty, respectively. In Panel A (Panel B), we report the results of regressions where the dependent variable is the AAA-Treasury (AAA-Treasury) corporate spread. Results from Eviews version 12.

Table 3.10 Quantile regression estimates [Growth-at-Risk]

			AAA20Y		
Quantile	*Q(0.05)*	*Q(0.25)*	*Q(0.5)*	*Q(0.75)*	*Q(0.95)*
GaR	0.07	0.11***	0.09**	0.17***	0.21**
	[1.26]	[3.37]	[2.26]	[2.72]	[2.49]
IP Growth	0.00	-0.02	-0.08**	-0.09**	-0.03
	[-0.12]	[-0.63]	[-2.46]	[-2.25]	[-0.43]
Log VXO	0.30***	0.31***	0.26***	0.25***	0.16*
	[5.11]	[7.00]	[4.95]	[3.09]	[1.70]
Sentiment	-0.38***	-0.19	0.07	0.43**	0.69**
	[-2.87]	[-1.60]	[0.48]	[2.49]	[2.31]
Stock Returns	0.04	-0.07	0.17	-0.13	-1.33
	[0.08]	[-0.17]	[0.32]	[-0.19]	[-1.25]
Tbill	-0.04***	-0.07***	-0.07***	-0.06***	-0.01
	[-3.81]	[-7.48]	[-10.50]	[-6.60]	[-0.77]
Treasury slope	-0.05**	-0.07***	-0.03	0.03	0.05
	[-2.22]	[-3.71	[-1.12]	[0.81]	[1.33]
Constant	1.59**	0.96*	0.04	-1.52	-2.31
	[2.48]	[1.65]	[0.05]	[-1.63]	[-1.53]
Pseudo R-squared	20.0%	29.5%	25.3%	21.8%	19.1%
			BAA20Y		
GaR	0.24***	0.34***	0.35***	0.29***	0.44***
	[3.53]	[6.20]	[5.04]	[3.20]	[3.60]
IP Growth	-0.04	-0.09**	-0.15***	-0.20***	-0.09
	[-1.24]	[-1.93]	[-3.12]	[-3.51]	[-0.91]
Log VXO	0.44***	0.52***	0.56***	0.73***	0.89***
	[9.01]	[7.20]	[9.54]	[6.56]	[7.14]
Sentiment	-1.00***	-0.86***	-0.58***	-0.39	-0.13
	[-5.26]	[-4.24]	[-3.03]	[-1.25]	[-0.35]
Stock Returns	1.05**	0.40	0.09	-0.28	0.70
	[2.06]	[0.53]	[0.12]	[-0.22]	[0.58]
Tbill	-0.10***	-0.09***	-0.09***	-0.08***	-0.10***
	[-6.47]	[-6.55]	[-7.71]	[-7.00]	[-6.92]
Treasury slope	-0.13***	-0.08***	-0.07**	0.00	0.05
	[-4.99]	[-3.63]	[-2.43]	[0.13]	[1.56]
Constant	5.05***	4.17***	3.03***	1.87	0.34
	[6.03]	[4.38]	[3.27]	[1.21]	[0.21]
Pseudo R-squared	38.9%	40.5%	39.5%	40.4%	61.0%

Notes: This table reports quantile regression coefficient estimates for the credit spreads. The t-statistics (in parentheses) are derived using bootstrapped standard errors. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively. GaR denotes growth-at-risk. The sample period is 1987M8–2019M12.

Table 3.11 Quantile regression estimates [Uncertainty]

			AAA20Y		
Quantile	*Q(0.05)*	*Q(0.25)*	*Q(0.5)*	*Q(0.75)*	*Q(0.95)*
UNC	0.11	0.14***	0.12***	0.22***	0.23***
	[1.59]	[3.41]	[2.46]	[3.57]	[2.91]
IP Growth	-0.02	-0.04	-0.08**	-0.10***	-0.12**
	[-0.83]	[-1.42]	[-2.81]	[-2.80]	[-2.00]
Log VXO	0.33***	0.33***	0.26***	0.24***	0.16**
	[5.42]	[8.11]	[5.12]	[3.08]	[2.07]
Sentiment	-0.36**	-0.24**	0.05	0.36**	0.66***
	[-2.46]	[-2.12]	[0.33]	[2.18]	[2.66]
Stock Returns	-0.08	0.17	0.24	-0.20	-0.01
	[-0.16]	[0.46]	[0.43]	[-0.32]	[-0.01]
Tbill	-0.04***	-0.06***	-0.07***	-0.06***	-0.01
	[-4.17]	[-7.00]	[-9.88]	[-6.15]	[-0.96]
Treasury slope	-0.06**	-0.07***	-0.03	0.03	0.05
	[-2.58]	[-3.66]	[-1.34]	[0.70]	[1.35]
Constant	1.29	0.94*	0.02	-1.39	-2.36*
	[1.71]	[1.64]	[0.03]	[-1.57]	[-1.91]
Pseudo R-squared	20.3%	29.9%	25.6%	22.1%	20.4%
			BAA20Y		
UNC	0.27***	0.45***	0.36***	0.40***	0.61***
	[4.10]	[6.16]	[4.77]	[3.48]	[4.23]
IP Growth	-0.07***	-0.16***	-0.22***	-0.21***	-0.12
	[-3.14]	[-3.61]	[-5.27]	[-3.84]	[-1.60]
Log VXO	0.39***	0.53***	0.62***	0.68***	0.93***
	[7.57]	[8.17]	[9.28]	[6.65]	[7.56]
Sentiment	-0.88***	-0.80***	-0.67***	-0.43	-0.37
	[-5.46]	[-4.00]	[-3.47]	[-1.63]	[-0.90]
Stock Returns	1.24**	0.38	0.36	0.17	1.14
	[2.38]	[0.56]	[0.38]	[0.15]	[0.86]
Tbill	-0.10***	-0.09***	-0.09***	-0.08***	-0.10***
	[-8.19]	[-7.12]	[-8.12]	[-6.69]	[-7.36]
Treasury slope	-0.14***	-0.10***	-0.07***	0.01	0.04
	[-6.94]	[-5.11]	[-2.63]	[0.31]	[1.08]
Constant	4.41***	3.47***	2.95***	1.74	0.76
	[6.28]	**[3.56]**	**[3.08]**	[1.30]	[0.43]
Pseudo R-squared	39.8%	40.5%	39.3%	40.4%	61.2%

Notes: This table reports quantile regression coefficient estimates for the credit spreads. The t-statistics (in parentheses) are derived using bootstrapped standard errors. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively. UNC denotes uncertainty. The sample period is 1987M8–2019M12.

Table 3.12 Quantile regression estimates [SKEW]

			AAA20Y		
Quantile	*Q(0.05)*	*Q(0.25)*	*Q(0.5)*	*Q(0.75)*	*Q(0.95)*
SKEW	-1.00**	-1.24***	-1.72***	-1.69***	-2.28***
	[-2.12]	[-3.66]	[-4.56]	[-3.21]	[-2.79]
IP Growth	-0.03	-0.05	-0.08**	-0.11***	-0.04
	[-1.04]	[-1.59]	[-2.93]	[-2.98]	[-0.61]
Log VXO	0.23***	0.33***	0.22***	0.18**	0.23**
	[3.43]	[7.75]	[4.49]	[1.97]	[2.16]
Sentiment	-0.43***	-0.19*	0.11	0.38**	1.02***
	[-2.79]	[-1.66]	[0.71]	[2.19]	[3.22]
Stock Returns	0.03	0.12	-0.26	-0.59	-0.72
	[0.06]	[0.27]	[-0.49]	[-0.93]	[-0.69]
Tbill	-0.03***	-0.06***	-0.06***	-0.06***	-0.03**
	[-3.19]	[-6.67]	[-9.28]	[-5.55]	[-2.18]
Treasury slope	-0.05**	-0.06***	-0.03	0.02	0.07
	[-2.17]	[-3.29]	[-1.09]	[0.60]	[1.60]
Constant	2.03***	0.98*	0.07	-0.94	-3.79**
	[2.96]	[1.74]	[0.10]	[-1.01]	[-2.43]
Pseudo R-squared	21.0%	30.8%	26.9%	22.8%	19.8%
			BAA20Y		
SKEW	-1.06***	-3.24***	-3.30***	-2.89***	-1.65*
	[-2.88]	[-6.05]	[-5.85]	[-3.91]	[-1.59]
IP Growth	-0.06**	-0.17***	-0.18***	-0.21***	-0.11
	[-2.39]	[-3.21]	[-4.37]	[-3.90]	[-1.08]
Log VXO	0.34***	0.46***	0.56***	0.56***	1.21***
	[6.87]	[6.89]	[7.82]	[4.51]	[6.91]
Sentiment	-0.96***	-0.75***	-0.66***	-0.55**	-0.88*
	[-5.85]	[-4.01]	[-3.33]	[-2.18]	[-1.70]
Stock Returns	0.83	-0.56	-0.10	-1.52	2.51*
	[1.50]	[-0.65]	[-0.14]	[-1.15]	[1.88]
Tbill	-0.10***	-0.08***	-0.09***	-0.09***	-0.12***
	[-6.70]	[-6.29]	[-8.19]	[-7.94]	[-7.53]
Treasury slope	-0.13***	-0.08***	-0.06***	-0.01	0.00
	[-5.44]	[-4.12]	[-2.16]	[-0.21]	[-0.03]
Constant	5.29***	4.15***	3.66***	3.29***	3.29
	[8.19]	[4.93]	[3.99]	[2.67]	[1.55]
Pseudo R-squared	37.8%	39.9%	39.6%	40.5%	59.3%

Notes: This table reports quantile regression coefficient estimates for the credit spreads. The t-statistics (in parentheses) are derived using bootstrapped standard errors. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively. SKEW denotes skewness. The sample period is 1987M8–2019M12. Results from EViews version 12.

Table 3.13 OLS regression estimates with principal component

Panel A

	AAA20YR	***AAA20YR***	***BAA20YR***	***BAA20YR***
MicroRisk	0.09***	0.05***	0.26***	0.14***
	[5.50]	[3.67]	[5.26]	[5.01]
IP growth		-0.06***		-0.14***
		[-3.42]		[-5.42]
log VXO		0.23**		0.60***
		[2.00]		[5.06]
Sentiment		0.10		-0.55
		[0.29]		[-1.64]
Stock return		-0.52		0.05
		[-1.31]		[0.09]
3-month Treasury yield		-0.06***		-0.08***
		[-3.11]		[-3.84]
Treasury slope		-0.03		-0.05
		[-0.60]		[-0.95]
Intercept	0.94***	0.06	1.90***	2.97*
	[16.14]	[0.04]	[30.27]	[1.85]
Adjusted-R^2	20.16%	38.33%	49.30%	71.33%

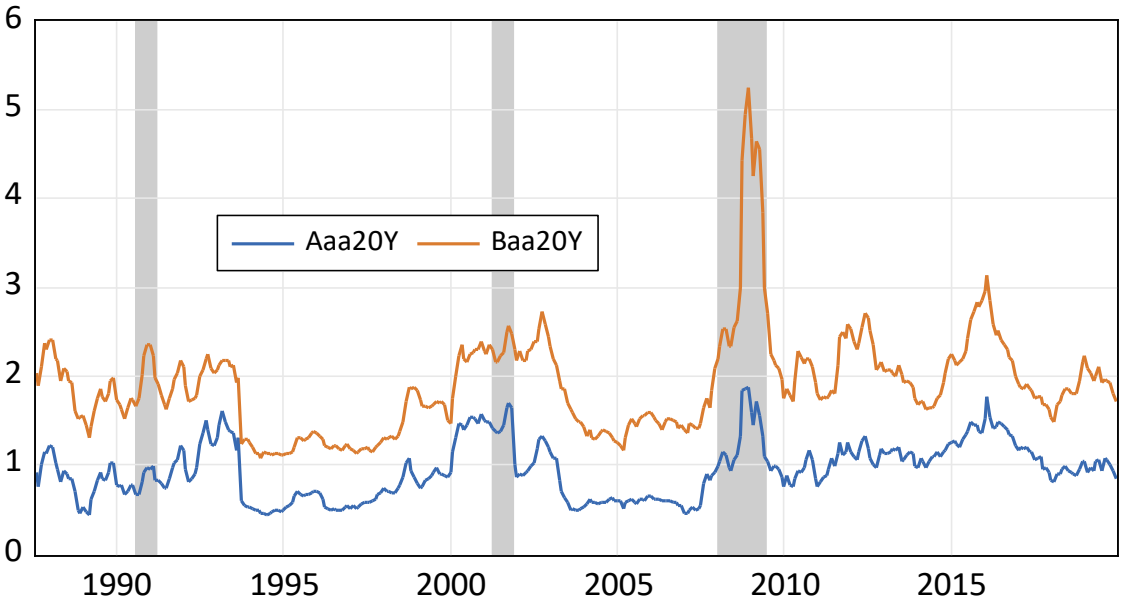
Panel B

	IG-OAS	***IG-OAS***	***HY-OAS***	***HY-OAS***
MicroRisk	0.42***	0.21***	1.27***	0.71***
	[4.44]	[4.36]	[6.75]	[7.48]
IP growth		-0.13***		-0.34***
		[-3.89]		[-4.04]
log VXO		0.91***		3.71***
		[6.20]		[8.70]
Sentiment		-1.77***		-1.54
		[-5.54]		[-1.39]
Stock return		0.00		0.02
		[0.37]		[0.99]
3-month Treasury yield		-0.10***		-0.24*
		[-3.14]		[-1.96]
Treasury slope		-0.11**		0.02
		[-2.25]		[0.10]
Intercept	1.50***	7.16***	5.38***	1.92
	[16.96]	[5.00]	[19.48]	[0.36]
Adjusted-R^2	59.96%	82.30%	59.32%	85.20%

Notes: The table reports OLS coefficients and t-statistics (in parentheses) for each regression model. OAS-IG and OAS-HY denote investment-grade and high-yield OAS, respectively. MicroRisk is the first principal component derived from GaR, UNC, and SKEW. We estimate the standard errors via a HAC Newey-West procedure. We use a Bartlett kernel and Andrews' automatic optimal bandwidth. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1987M8–2019M12.

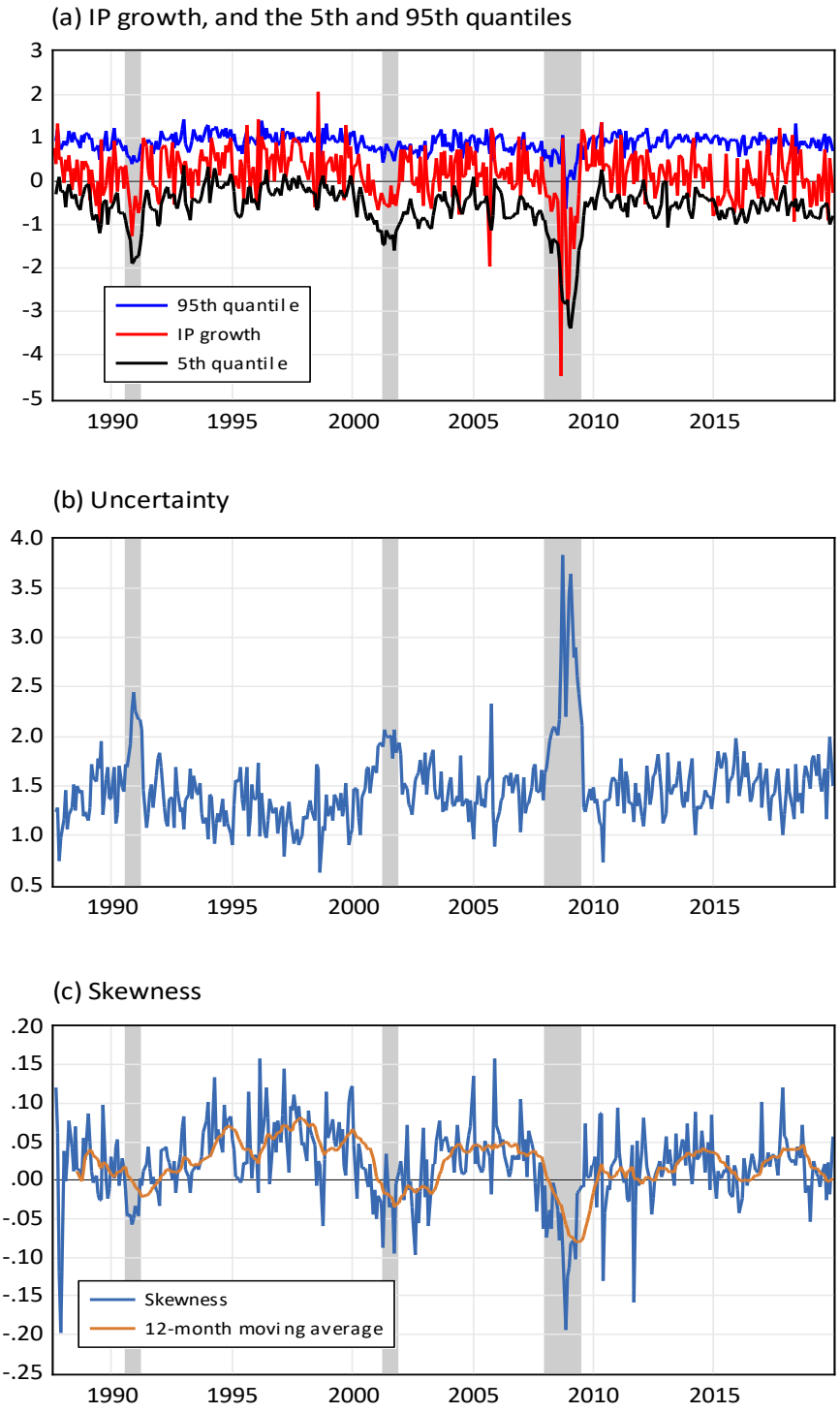
3.6.2 Figures

Figure 3.1 Corporate credit spreads



Notes: This figure plots the time series of Moody's Aaa-Treasury (Aaa20Y) and Baa-Treasury (Baa20Y) credit spreads for the period 1987M08-2019M12. The shaded regions are the NBER recession periods.

Figure 3.2 IP growth risk measures



Note: Panel (a) plots IP growth and its 5th and 95th. The middle panel (b) shows the Uncertainty measure. The bottom panel (c) displays the time series of IP growth Skewness. The shaded areas represent NBER recession months.

Figure 3.3 Scree Plot (Ordered Eigenvalues)

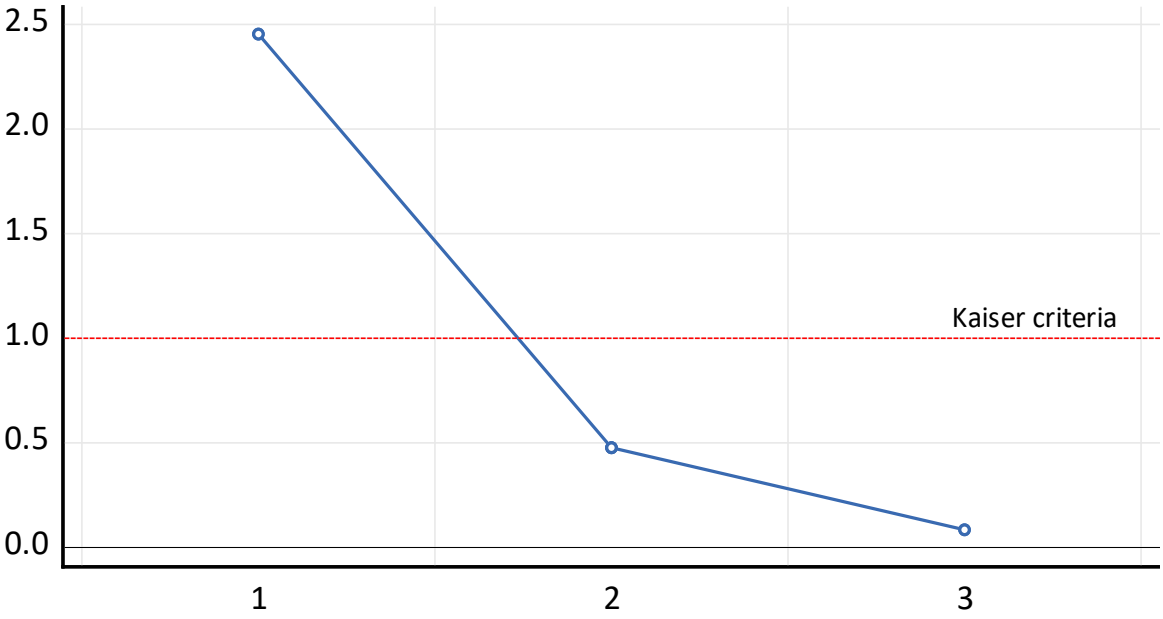


Figure 3.4 Orthonormal Loadings

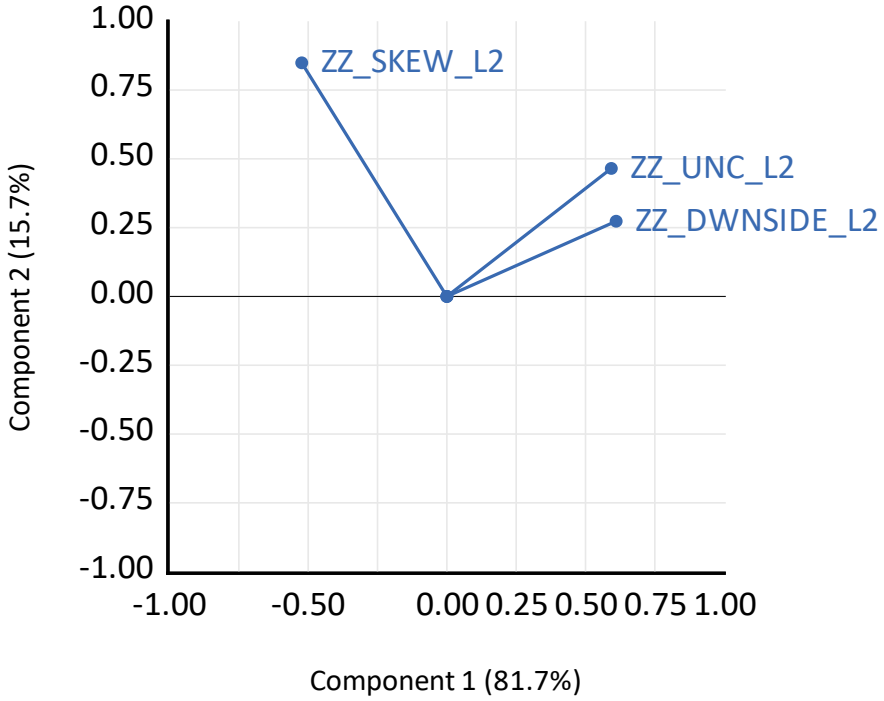
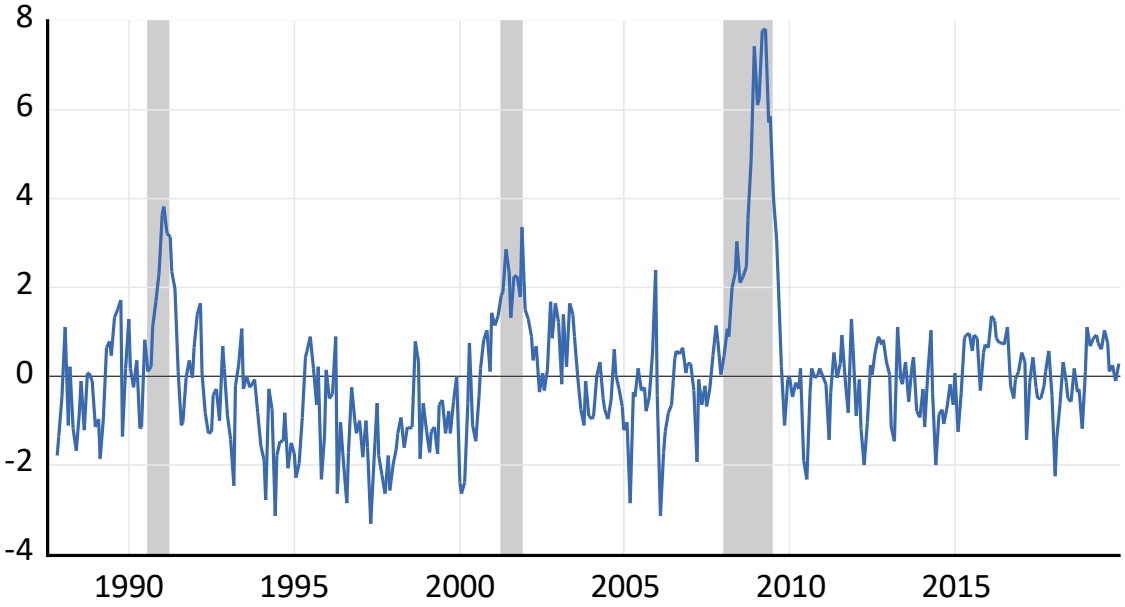


Figure 3.5 Time series of the first principal component



The gray bars are recessions as determined by NBER's Business Cycle Dating Committee.

3.7 Appendix B

B.1 Merton's model of corporate debt

The three key assumptions of Merton (1974) are that assets trade in continuous time; the Modigliani-Miller (1958) theorem that firm value is based on its future earnings, while it is invariant to its capital structure; and the dynamics of the firm value through time can be described by a diffusion-type stochastic process. We have the geometric Brownian Motion process

$$dV_t = V_t([r - \gamma]dt + \sigma V_t dW_t) \tag{3.12}$$

where V_t is the firm value with an initial value greater than zero; r is the expected rate of return for the firm; γ is dividend and interest payouts to shareholders and bondholders, respectively; σ is the standard deviation of return; and W_t is a standard Brownian motion under the (risk-neutral) martingale measure Q. According to Merton, the perfect market assumptions, including frictionless markets (no transaction costs or taxes), perfectly divisible assets, no borrowing-lending spread, short-selling of all assets allowed, and a sufficient number of investors, are easily relaxed (Sundaresan, 2013).

Under these assumptions, default can only occur at maturity, date T, when the value of the firm's assets V_T is insufficient to meet the obligations to the debt holders B. At the maturity of the debt obligation, debt holders realise an amount V_T in the event of a default ($V_T < B$), or the face value B, otherwise. Formally, the payoff to the creditors at time T is

$$D(V_T, B) = min(V_T, B) = B - max(B - V_T, 0). \tag{3.13}$$

The debt holder's claim is equivalent to a portfolio comprising a default-free bond with face value B, and short a put option written on the firm's assets with a strike price K equal to B.

The value of the riskless discount bond promising to pay \$1 at time T in the future is $P(t,T) = e^{-r(T-t)}$, where r is the (instantaneous) risk-free rate of interest. Define $N(\cdot)$ as the standard Gaussian cumulative distribution function as $N(x) = \frac{1}{\sqrt{2\pi}}\int_{\infty}^{x} e^{-\frac{y^2}{2}}dy$. Then the corporate debt value is

$$D(t,T) = V_t e^{-\gamma(T-t)}N(-d_1) + BP(t,T)N(d_2) \tag{3.14}$$

where

$$d_1 = \frac{ln\left(\frac{V_t}{B}\right) + \left(r - \gamma + \frac{1}{2}\sigma^2\right)(T-t)}{\sigma\sqrt{T-t}} \tag{3.15}$$

and

$$d_2 = d_1 - \sigma\sqrt{T-t}. \tag{3.16}$$

Defining leverage as $k = \frac{Be^{-r(T-t)}}{V_t}$ and letting $\tau = T - t$, Merton's model computes the corporate credit spread $CS = R(\tau) - r$ as follows

$$CS = -\frac{1}{\tau} ln\left[V_t e^{-\gamma(T-t)} N(-d_1) + BP(t,T)N(d_2)\right] \tag{3.17}$$

here the yield to maturity of the risky zero-coupon bond is defined as $D(t,T) \equiv e^{-R(\tau)\tau}$. The probability of default, in the risk-neutral probability measure, is computed as

$$\text{Default probability} \equiv P(V_t < B) \equiv \pi_Q = N(-d_2)$$

and the expected (discounted) recovery rate as

$$Expected\ discounted\ recovery\ rate = E^Q\left[e^{-r(T-t)}\frac{V_t}{B}|V_t < B\right].$$

Assuming the expected return of the firm's assets is μ, Merton's model computes the probability of default, π_p, in the physical measure as $\pi_p = N(-d_2')$, where

$$d_2' = \frac{ln\left(\frac{V_t}{B}\right) + \left(\mu - \gamma - \frac{1}{2}\sigma^2\right)(T-t)}{\sigma\sqrt{T-t}} \tag{3.18}$$

The relationship between the risk-neutral probability of default and the physical probability of default is given by $\pi_Q = N\left(N^{-1}(\pi_p) + \frac{\mu - r}{\sigma}\sqrt{\tau}\right)$.

B.2 Quantile regressions

The theoretical quantiles $Q_Y(\tau)$, $\tau \in (0,1)$ of a random variable Y are defined as:

$$P(y \le Q_Y(\tau)) \ge \tau \quad \text{and} \quad P(y \ge Q_Y(\tau)) \ge 1 - \tau, \tag{3.19}$$

that is, τ is the probability of observing a realisation below (or equal to) $Q_Y(\tau)$ while $1 - \tau$ is the probability of a realisation above (or equal to) $Q_Y(\tau)$.The conditional quantile function of Y given X is the inverse of the corresponding conditional cumulative distribution function, that is,

$$Q_Y(\tau|X) = F_Y^{-1}(\tau|X) = inf\{y: F_Y(y|X) \ge \tau\}, \tag{3.20}$$

where $F_Y^{-1}(\tau|X) = P(Y \leq y|X)$. The conditional quantile function provides a complete description of the whole conditional distribution. Considering a random variable Y with a distribution function $F(y)$, the τ-th quantile of Y is defined by

$$Q_Y(\tau|X) = inf\{y|F(y) \geq \tau\}, \tag{3.21}$$

Let us consider a random sample $\{y_1, \dots, y_n\}$ from the cumulative distribution function $F(y)$ such that $0 \leq F(y) \leq 1$ is by construction a non-negative function. The τ-th sample quantile can be defined as

$$\hat{Q}_Y(\tau|X) = inf\{y|\hat{F}(y) \geq \tau\}. \tag{3.22}$$

ere $\hat{F}$ is the empirical distribution function of the random sample.

Let us consider the standard linear regression model taking the form

$$Y_t = \beta' X_t + u_t \tag{3.23}$$

where X_t is a vector of k lagged predictors (also including the lag of the dependent variable) plus the intercept term, and u_t is an independent and identically distributed $(i.i.d.)$ sequence of mean zero random variables with distribution function $F(\cdot)$. The conditional distribution of Y_t is a location shift of $F(\cdot)$, with conditional mean $\beta' X_t$. Thus, with quantile regression, the τ-th conditional quantile of Y_t is a linear function of X_t, that is,

$$Q_{Y_t}(\tau|X_t) = \beta' X_t + F_u^{-1}(\tau) = \beta(\tau)' X_t \tag{3.24}$$

where $\beta(\tau)' = (\beta_1 + F_u^{-1}(\tau), \beta_2, \dots, \beta_k)$. Koenker and Bassett (1978) show that the τ-th conditional regression quantile can be estimated by:

$$\hat{Q}_{Y_t}(\tau|X_t) = \hat{\beta}(\tau)' X_t \tag{3.25}$$

where the regression slopes $\hat{\beta}(\tau)$ are obtained by minimising the quantile-weighted absolute value of errors:

$$\hat{\beta}(\tau) = \underset{\beta \in R^k}{arg\,min} \left[\sum_{t \in \{t: y_t \geq x_t \beta\}} \tau |y_t - \beta(\tau)' x_{t-1}| + \sum_{t \in \{t: y_t < x_t \beta\}} (1-\tau) |y_t - \beta(\tau)' x_{t-1}| \right]. \tag{3.26}$$

Let $\rho_\tau(u) = u\big(\tau - I(u < 0)\big)$, a non-differentiable quantile weighted loss function, then

$$\hat{\beta}(\tau) = \underset{\beta \in R^k}{arg\,min} \sum_t \rho_\tau(y_t - \beta(\tau)' x_{t-1}). \tag{3.27}$$

The check function $\rho_\tau(u)$ replaces the traditional quadratic loss used for mean regression. Optimisation of the loss function is done using linear programming methods.

B.3 Generalized Method of Moments (GMM) with over-identified parameters

Suppose that a sample of T observations $(w_1, w_2, \dots, w_T)$ is drawn from the joint distribution function (Pesaran, 2015)

$$g(s_1, s_2, \dots, s_T; \theta_0), \tag{3.28}$$

where θ_0 is a $p \times 1$ vector of true parameters from the parameter space, Θ. Typically, s_t would contain one or more endogenous variables. Let $m(\cdot)$ be a j-dimensional vector of functions so that the population moment condition is of the form

$$E[m(s_t, \theta_0)] = 0, \text{for all } t. \tag{3.29}$$

The model is exactly identified if the number of moment conditions j equals the number of unknown parameters p in θ, that is, $j = p$. The model is over-identified if $j > p$.

The GMM estimator $\hat{\theta}$ is based on the empirical counterpart of $E[m(s_t, \theta_0)]$, a solution of the j equations obtained by replacing the population mean E in Eq (27) by the sample mean $\frac{1}{n}\sum_{t=1}^{T}$ to give a j-dimensional vector of sample moments

$$M_T(\theta) = \frac{1}{T}\sum_{t=1}^{T} m(s_t, \theta)\,. \tag{3.30}$$

An over-identified case, with more equations than unknown parameters, requires the moment conditions to be restricted to obtain a unique parameter vector in the estimation. An efficient approach to estimation combines all the available moment conditions using the GMM estimator of θ given by

$$\hat{\theta}_T = arg\min_{\theta \in \Theta}\{M_T'(\theta) W_T M_T(\theta)\}\,, \tag{3.31}$$

where W_T is a $j \times j$ symmetric and positive semi-definite weighting matrix that is assumed to converge to a unique, positive definite, non-random matrix, that is, $W_T \xrightarrow{p} W$. A unique parameter vector $\hat{\theta}_T$ is obtained by imposing weights on the j moment conditions. The first-order conditions for minimisation are

$$D_T'(\hat{\theta}_T) W_T M_T(\hat{\theta}_T) = 0 \tag{3.32}$$

where

$$D_T'(\hat{\theta}_T) = \frac{\partial}{\partial \theta'} M_T(\theta) = \frac{1}{T}\sum_{t=1}^{T} \frac{\partial}{\partial \theta'} m_T(\theta) \tag{3.33}$$

is a $j \times p$ matrix of first-order derivatives.

For the linear regression specification, we have the residuals $u_t = y_t - x_t'\beta$. We consider moment conditions satisfying the orthogonality condition between the residuals and a set of k instrumental variables (IV) z_t:

$$E[z_t u_t] = 0, \qquad t = 1, 2, \dots, T \tag{3.34}$$

The GMM estimator replaces the expectation E by the sample mean so that

$$\frac{1}{T}\sum_{t=1}^{T} z_t u_t = 0, \tag{3.35}$$

and finds the parameter vector β which solves the set of j moments. For an overidentified system, the GMM objective function is given by

$$J(\beta, W_T) = \frac{1}{T}(y - X\beta)' Z W_T Z' (y - X\beta) \tag{3.36}$$

and the GMM estimator yields the unique solution $\hat{\theta} = (X'ZW_TZ'X)^{-1}X'ZW_TZ'y$. The asymptotic covariance is given by

$$V_W = (\Sigma' W_T \Sigma)^{-1} \cdot \Sigma' W_T S W_T' \Sigma \cdot (\Sigma' W_T' \Sigma)^{-1} \tag{3.37}$$

where $S = \operatorname{plim} \frac{1}{T} Z'uu'Z$, the asymptotic variance of $\sqrt{T} M_T(\hat{\beta})$ and the long-run covariance matrix of the vector process $\{Z_t u_t\}$, and $\Sigma = \operatorname{plim} \frac{1}{T}(Z'X)$. The weighting matrix W_T which should lead to asymptotic efficiency of the GMM estimator is chosen to minimise the covariance matrix V_W.

Implementing optimal GMM estimation requires specifying a weighting matrix. A two-stage least squares weighting matrix given by $\widehat{W}_T = \hat{\sigma}^2 Z'Z/T$ is used, where $\hat{\sigma}^2$ is an estimator of the residual variance. The computation of robust standard errors is based on the HAC (Newey-West) estimator with the Bartlett kernel and Andrew's automatic bandwidth selection technique.

B.4 The Hausman LM-test exogeneity test

It is useful to have a test for endogeneity of explanatory variables to justify the instrumental variable approach since this approach is less efficient than OLS. We perform the Hausman LM-test on exogeneity as follows (see Heij et al., 2004):

Step 1: Preliminary regressions. Regress y on X to get a $T \times 1$ residual vector $u = y - X\beta$. Regress every possible endogenous explanatory variable x_q on instruments Z, with $T \times 1$ residual vector $\hat{\eta}_q = x_q - Z\hat{\lambda}_q$.

Step 2:Auxillary regression. Since each instrument is uncorrelated with u, the k_0 regressors are uncorrelated with u if $\hat{\eta}_q$ is uncorrelated with u. Therefore, regress u on X (the $T \times k$ matrix including both the $(k - k_0)$ exogenous and the k_0 possibly endogenous regressors) and on the k_0 series of residuals $\hat{\eta}_{k-k_0+1}, \dots, \hat{\eta}_k$. The estimated OLS model is

$$u_i = \sum_{q=1}^{k} \delta_q x_{qi} + \sum_{q=k-k_0+1}^{k} \alpha_q \hat{\eta}_{qi} + \varrho_i \,. \tag{3.38}$$

We test $H_0: \alpha_q = 0$ using t-statistics. Endogeneity of the regressors is indicated by a significant estimate of the parameters α_q, that is, by rejection of H_0 at the 5% significance level.

Step 3: $LM = TR^2$ of the regression in step 2. R^2 is the coefficient of determination of the regression in step 2. Under the null hypothesis that all k_0 regressors x_q, $q = k - k_0 + 1, \dots, k$, are exogenous, LM has asymptotically the $\chi^2(k_0)$ distribution.

B.5 ARMA-GJR-GARCH model

The IP growth-at-risk and volatility risk measures are constructed based on the GARCH-type specification:

$$Y_t = \mu_{t|t-1} + \sqrt{\sigma^2_{t|t-1}}\mathrm{Z}_t \qquad \mathrm{Z}_t \underset{i.i.d}{\sim} \mathfrak{D}_Z(0,1) \tag{3.39}$$

where $\mu_{t|t-1}$ denotes the time t conditional mean, $\sigma^2_{t|t-1}$ is the time t conditional variance and $\mathfrak{D}_Z(\mu, \sigma^2)$ is the location-scale distribution with mean μ and variance σ^2. The time t conditional distribution of IP growth rates implied by Eq. (37) is

$$Y_t|\mathcal{F}_{t-1} \sim \mathfrak{D}_Z\left(\mu_{t|t-1}, \sigma^2_{t|t-1}\right) \tag{3.40}$$

indicating that the innovation distribution $\mathfrak{D}_Z$ determines the shape of the conditional distribution. The time t τ% conditional quantile of $\{Y_t\}$ is therefore given by

$$Q_\tau(Y_t|\mathcal{F}_{t-1}) = \mu_{t|t-1} + \sqrt{\sigma^2_{t|t-1}} F_Z^{-1}(\tau) \tag{3.41}$$

where $F_Z^{-1}(\tau)$ is the inverse cumulative distribution function of $\mathfrak{D}_Z$ and $\mathcal{F}_{t-1}$ is the σ-field generated by all the available information up through time $t-1$. For the conditional mean, we consider the following autoregressive moving average model, denoted as ARMA(p,q)

$$Y_t = \delta + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_{t,} \tag{3.42}$$

where δ is a constant term, ϕ_i the ith autoregressive coefficient, θ_j the jth moving average coefficient, ε_t the error term at time t, and p and q are the orders of the autoregressive and moving-average terms, respectively.

The conditional variance equation is key to constructing the volatility and quantile risk measures. We consider the GJR-GARCH(1,1) of Glosten et al. (1993), which evolves according to:

$$\sigma^2_{t|t-1} = \omega + \left(\alpha + \gamma I_{[\varepsilon_{t-1}<0]}\right)\varepsilon^2_{t-1} + \beta\sigma^2_{t-1|t-2}, \tag{3.43}$$

where the indicator function $I_{[\varepsilon_{t-1}<0]}$ takes the value of 1 when the lagged shock is negative and zero otherwise. It must be that $\omega > 0$, $\alpha \geq 0$, $\alpha + \gamma \geq 0$ and $\beta \geq 0$. The term γ_j captures asymmetry with negative news having a greater influence on volatility when $\gamma > 0$. Thus, the effect of a negative shock on conditional variance is given by $(\alpha + \gamma)$ and a positive shock by α. Our application assumes the Student's *t*-distribution, which is specified as:

$$f(\varepsilon_t|\mathcal{F}_{t-1}) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)[\pi\sigma_t^2(\nu-2)]^{1/2}}\left(1 + \frac{\varepsilon_t^2}{(\nu-2)\sigma_t^2}\right)^{-\left(\frac{\nu+1}{2}\right)}, \qquad \nu > 4 \tag{3.44}$$

with excess kurtosis equal to $6/(\nu-4)$ where ν is the degrees of freedom and $\Gamma(\cdot)$ is the gamma function. We estimate the GARCH GaR using the formula:

$$GaR_{t,\tau} = \mu_{t|t-1} + t_{\nu,\tau} * \sqrt{\sigma^2_{t|t-1} * \frac{\nu-2}{\nu}} \tag{3.45}$$

$t_{\nu,\tau}$ is the quantile of Student's t-distribution with ν degrees of freedom.

B.6 Principal Component Analysis

An approach suggested to ameliorate multicollinearity is to use a small number of principal components (PCs) constructed as linear combinations of the original variables (see Guidolin and Pedio, 2018).

Given a K-dimensional random vector $\mathbf{x} \equiv [x_1 x_2 \cdots x_K]'$ with the covariance matrix $\Sigma_{\mathbf{x}}$ and correlation matrix ρ_x, principal component analysis (PCA) uses a few linear combinations of the variables $x_i (i = 1, 2, \dots, K)$ to explain the structure of Σ_x or ρ_x. Let $h_i = \left[h_{i,1}, h_{i,2}, \dots, h_{i,K}\right]'$ be a K-dimensional vector, where $i = 1, 2, \dots, K$. Then

$$PC_i = h_i' \mathbf{x} = \sum_{n=1}^{m} h_{in} x_n \,. \tag{3.46}$$

For the covariance of PC_i we have:

$$Var(PC_i) = h_i' \Sigma_x h_i \quad i = 1, \dots, m \,\#(3.47)$$

$$Cov(PC_i, PC_n) = h_i' \Sigma_x h_n \quad i, n = 1, \dots, m. \tag{3.47}$$

PC orders the linear combinations $h_i' \mathbf{x}$ by their contribution to variance, with the principal components mutually uncorrelated. More specifically:

1. The first principal component is the linear combination $PC_1 = h_1' \mathbf{x}$ that maximises $Var(PC_1)$ subject to the constraint $h_1' h_1 = 1$.
2. The second principal component is the linear combination $PC_2 = h_2' \mathbf{x}$ that maximises $Var(PC_2)$ subject to the constraint $h_2' h_2 = 1$ and $Cov(PC_2, PC_1) = 0$.
3. The *i*th principal component of the data **x** is the linear combination $PC_i = h_i' \mathbf{x}$ that maximises $Var(PC_i)$ subject to the constraint $h_i' h_i = 1$ and $Cov(PC_i, PC_n) = 0$ for $n = 1, \dots, i - 1$.

Since the symmetric covariance matrix $\Sigma_{\mathbf{x}}$ is positive definite; it has a spectral decomposition whereby it can be expressed in terms of its eigenvalues and eigenvectors. Subtracting a scalar λ from each diagonal element of $\Sigma_{\mathbf{x}}$ (similar to subtracting λ times the identity matrix **I** from Σ_x) yields a singular matrix $\Sigma_{\mathbf{x}} - \lambda \mathbf{I}$ such that a system of equations $(\Sigma_{\mathbf{x}} - \lambda \mathrm{I})\mathbf{z} = 0$ has a solution other than $\mathbf{z} = 0$. Thus, a nonzero vector $\mathbf{z}$ is an eigenvector of $\Sigma_{\mathbf{x}}$ corresponding to the eigenvalue λ.

Since the covariance matrix $\Sigma_{\mathbf{x}}$ is positive semi-definite, the eigenvalues are real and positive, and the eigenvalues are real, non-negative, and ordered $\mathbf{z}_1 \geq \mathbf{z}_2 \geq \cdots \geq \mathbf{z}_K \geq 0$. Let PC $= (PC_1, \dots, PC_K)$ be the principal components of **x**. We also have $\mathbf{z}_i' \mathbf{z}_i = 1$ and

$\mathbf{z}_i'\mathbf{z}_n = 0$ (i.e., the eigenvectors are orthogonal to each other). The variance of the *i*th PC of $\mathbf{x}$ is

$$\text{var}(PC_i) = \text{var}\left(h_i^i\mathbf{x}\right) = h_i^i\Sigma_{\mathbf{x}}\boldsymbol{h_i} = \mathbf{z}_i \qquad i = 1, \dots, m$$

$$\text{cov}(PC_i, PC_n) = h_i^i\Sigma_{\mathbf{x}}\boldsymbol{h_j} = 0 \qquad i \neq n. \tag{3.48}$$

Also,

$$\sum_{i=1}^{K}\text{var}(x_i) = tr(\Sigma_{\mathbf{x}}) = \sum_{i=1}^{K}\lambda_i = \sum_{i=1}^{K}\text{var}(PC_i) \tag{3.49}$$

such that the relative variance contribution of the *i*th principal component is

$$\frac{\text{var}(PC_i)}{\sum_{i=1}^{K}\text{var}(x_i)} = \frac{\lambda_i}{\lambda_1 + \cdots + \lambda_K}. \tag{3.50}$$

Principal components are sensitive to the scaling of $\mathbf{x}$ hence it is recommended to first scale each element of $\mathbf{x}$ to have mean zero and unit variance, in which case $\Sigma_{\mathbf{x}}$ is a correlation matrix (see Guidolin and Pedio, 2018).

The sample PCs are obtained by replacing the unknowns with sample estimators. The unknown covariance matrix $\Sigma_{\mathbf{x}}$ and correlation matrix ρ_x can be estimated consistently by the sample covariance and correlation matrices given by

$$\hat{\Sigma}_{\mathbf{x}} \equiv \hat{\sigma}_{in,\mathbf{x}} = \frac{1}{T-1}\sum_{t=1}^{T}(\mathbf{x}_t - \bar{\mathbf{x}})(\mathbf{x}_t - \bar{\mathbf{x}})' \qquad \bar{\mathbf{x}} = \frac{1}{T}\sum_{t=1}^{T}\mathbf{x}_t$$

$$\hat{\rho}_{\mathbf{x}} = \widehat{\mathbf{D}}^{-1}\hat{\Sigma}_{\mathbf{x}}\widehat{\mathbf{D}}^{-1'} \tag{3.51}$$

where $\widehat{\mathbf{D}} \equiv \text{diag}\left\{\sqrt{\hat{\sigma}_{11,\mathbf{x}}}, \dots, \sqrt{\hat{\sigma}_{KK,\mathbf{x}}}\right\}$ is a diagonal matrix of sample standard errors of $\mathbf{x}_t$.

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4 Sovereign credit default swaps in commodity-exporting countries

4.1 Introduction

Sovereign debt has played a crucial role in helping governments recover after the global financial crisis (GFC) and the COVID-19 pandemic, offering essential funds for deficit spending and stimulus initiatives to soften economic shocks. By 2022, public debt levels had risen to around 120 per cent of GDP in advanced economies and 64 per cent in emerging and developing countries (Kose et al., 2021a). Governments with high debt levels face numerous risks, such as falling commodity prices and trade conflicts, which might lead to widespread debt crises and defaults. Such scenarios could cause a sharp increase in global interest rates, elevate risk premiums, or significantly slow economic growth (Kose et al., 2021b). As a result, concerns about sovereign creditworthiness and the possibility of default remain significant in both developing and advanced economies.

During the commodity boom of the 2000s, many commodity-exporting countries maintained healthy fiscal balances and low debt levels (Rashid et al., 2020). However, according to the World Bank (2024), from 2010 to 2022, the debt levels of commodity-exporting emerging economies increased rapidly from about 33% to approximately 58% of GDP. The sharp fluctuations in global commodity prices in recent years, coupled with high debt-servicing costs and weaker growth prospects, raise the likelihood of debt distress and defaults (Arezki and Brückner, 2012; Reinhart et al., 2016; Boehm et al., 2021). The 2020 Fitch report notes that the collapse in commodity prices between 2014 and 2016 contributed to an increase in sovereign downgrades and defaults among emerging markets.[22]

This chapter explores how fluctuations in commodity prices affect sovereign credit risk in countries heavily dependent on commodity exports. Commodity exports are a vital source of fiscal revenue and export income for such nations, impacting consumption,

[22] https://www.fitchratings.com/research/sovereigns/oil-shock-compounds-sovereign-credit-risks-from-coronavirus-09-03-2020

investment, and overall economic activity. Economic agents evaluating the likelihood of future debt problems that could lead to default regard global commodity prices as a key indicator of economic outlook, guiding their decisions (Bastourre et al., 2012). Policymakers worry about potential debt distress and its effects on financial and macroeconomic stability. Investors aim to manage their exposure to sovereign risk to protect the value of their investments.

Although there is extensive research on sovereign credit risk, studies specifically focusing on commodity-export-dependent nations remain limited. These countries have gained more prominence recently, as the UNCTAD (2023) reports that over 50% of global economies rely heavily on commodity exports. The report also emphasises that commodity dependence is not confined to emerging and developing nations, with around 13% of advanced economies also characterised by this dependence.

Traditionally, advanced economies (AEs) are seen as less likely to default on their debt compared to emerging economies (EMEs), due to their stronger economies and more effective institutional frameworks for managing crises (Reinhart et al., 2003; Hilscher and Nosbusch, 2010; Mitchener and Trebesch, 2023). The sovereign debt crises of the 1980s and 1990s prompted increased research into sovereign risk dynamics in emerging and developing economies. However, the GFC and the Eurozone debt crisis exposed a decline in the creditworthiness of some advanced economies, highlighting that debt sustainability remains a concern irrespective of a country's level of economic development (Mitchener and Trebesch, 2023). In 2016, YaleGlobal expressed concern over Australia's rising external debt, noting it had become dangerously high and was imposing a substantial interest burden amidst low commodity prices.[23]

We analyse four countries heavily dependent on commodity exports: two developed economies, Australia and Norway, and two emerging markets, Brazil and Russia. Besides their differing levels of economic development and commodity export baskets, they also have diverse institutional and fiscal frameworks and have all established sovereign wealth funds with various degrees of success. During the period studied, they achieved different credit ratings and displayed distinct geopolitical characteristics.

Investors take into account country classification and economic stage when evaluating different sovereign borrowers (Brooks et al., 2015). Sovereign defaults often occur during economic downturns, when output and revenues decline sharply (Tomz and

[23] https://archive-yaleglobal.yale.edu/content/australia-foreign-debt-reaches-crisis-proportions

Wright, 2007). The influence of risk factors on sovereign credit risk varies over time, possibly due to shifting economic cycles, crises, and investors' risk aversion (Bernoth and Erdogan, 2012; Heinz and Sun, 2014; Delatte et al., 2017). Blommestein et al. (2016) note that the sovereign credit default swap (CDS) market in certain Eurozone countries alternates between crisis and non-crisis states. Boehm et al. (2021) observe that reliance on commodity exports for sovereign financing in commodity-dependent emerging economies increases during recessions. When assessing fiscal sustainability, market participants are therefore likely to pay closer attention to global commodity market developments during crises than in stable times. Consequently, we expect the sensitivity of sovereign credit risk in commodity-exporting countries to commodity prices to depend on the regime.

We employ a Markov-switching dynamic regression model to examine how global commodity prices influence sovereign credit risk in commodity-exporting countries. We posit that the effect of commodity price fluctuations on sovereign risk may vary with the unobservable economic state. The Markov-switching model characterises the behaviour of a time series variable in the presence of structural breaks or regime shifts, utilising state-dependent parameters to reflect these changes and other multi-state phenomena. Transitions between unobserved states follow a Markov chain (Hamilton, 1989). This approach effectively captures non-linear dynamics and the asymmetric behaviours observed across various states. Relying on standard linear models to analyse the determinants of sovereign credit risk, which assume a constant relationship, can fail to capture nonlinearities and may result in misleading conclusions (Hamilton, 1989).

Our measure of sovereign credit risk is the five-year sovereign CDS spread. Sovereign CDS (SovCDS) spreads act as market-based, forward-looking indicators of perceived default risk, capturing investor sentiment and expectations about the sovereign borrower's fiscal health and macroeconomic fundamentals in a single metric. Therefore, this credit derivative reflects the economic fundamentals and market conditions associated with the underlying sovereign credit risk (IMF, 2013). Unlike sovereign bond yield spreads, CDS spreads offer better cross-country comparability because they have a consistent definition of horizon, restructuring clauses, and currency, without complicated covenants or embedded options (Pan and Singleton, 2008; Augustin et al., 2016). Furthermore, sovereign CDS are generally more liquid than government bonds, enabling markets to quickly incorporate new information during periods of financial stress, thus providing a real-time view of a sovereign's creditworthiness (Longstaff et al., 2011; Ang and Longstaff, 2013; IMF, 2013).

We analyse weekly data from December 2008 to 18 February 2022. Consistent with recent research, we incorporate both global and country-specific financial indicators as control variables. The availability of high-frequency financial data provides enough variability to identify factors influencing sovereign credit spreads (Blommestein et al., 2016). According to Blommestein et al., financial data reflect agents' expectations about future macroeconomic developments, while real-time macroeconomic data reflect only past information.

In our empirical analysis, the chapter examines the following questions: First, does sovereign credit risk in commodity-export-dependent countries respond differently to global commodity prices depending on the regime? Second, do commodity price fluctuations similarly influence SovCDS spreads in both advanced and emerging economies? Mitchener and Trebesch (2023) note that emerging economies have experienced significant wealth growth and expansion of their financial sectors, with efforts to strengthen macroeconomic stability boosting their creditworthiness (Amstad and Packer, 2015). Born et al. (2020) suggest that sovereign spread dynamics across emerging and advanced economies have since converged after the GFC, as advanced economies have become increasingly vulnerable to shocks. Lastly, what information variables can explain the regime switching?

This chapter makes at least three significant contributions to research on the factors influencing changes in sovereign credit risk. Firstly, we contribute to the limited literature examining the sovereign risk of resource-rich countries. Our country selection includes Australia and Norway, advanced economies dependent on commodity exports, which are rarely the focus of sovereign credit risk studies in existing research. Studying a group of advanced and emerging economies that rely on exports of different commodities allows us to compare how these countries' sovereign risk responds to shifts in global commodity markets. Secondly, we enhance the literature by assessing the nonlinearity in the response of SovCDS spreads to changes in commodity prices. Most existing studies rely on single-regime linear regression methods. We also provide empirical evidence on the significance of certain indicators in influencing the evolution of transition probabilities over time. Lastly, we employ the Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI) to measure global commodity prices, contrasting it with prior research primarily focusing on oil prices (e.g., Chuffart and Hooper, 2019; Aizenman et al., 2016; Naifar et al., 2020). The S&P GSCI is a well-established benchmark representing a broad range of internationally priced commodities.

Our findings indicate that increases in global commodity prices significantly decrease the sovereign CDS spreads of all sampled economies, with the magnitude of these effects varying across economies. The reduction in SovCDS spreads when commodity prices rise is statistically significant for Australia, Brazil, and Russia across both regimes. Conversely, for Norway, results suggest that the narrowing of spreads is significant only during high-volatility (crisis) periods. We observe greater sensitivity to commodity fluctuations during turbulent times, suggesting that falling commodity prices during such periods lead to a larger widening of SovCDS spreads than during stable times. Moreover, SovCDS spreads for emerging economies are more sensitive to commodity price changes across regimes than those for advanced economies. Commodity price variations have the least impact on Norway's SovCDS spreads during both regimes, and the greatest on Russia's. These results emphasise the importance of considering non-linear effects when analysing the influence of commodity prices on SovCDS spreads.

Additional analyses using a Markov-switching model with time-varying transition probabilities (TVTP) support our main findings. The TVTP approach also helps identify variables that affect regime shifts. We investigate whether transition probabilities vary with lagged changes in commodity prices and global financial stress. Results show that rising global financial stress, as measured by the Office of Financial Research (OFR) Financial Stress Index (FSI), increases the likelihood of a transition to a crisis state in Australia, Brazil, and Russia. Times of heightened global financial stress make market participants more alert and scrutinise sovereign fundamentals, leading to increased market activity as higher risk aversion causes investors to demand greater premiums or reduce exposure to risky assets, thereby boosting market volatility. Estimates also suggest that changes in global commodity prices tend to increase the likelihood of remaining in a low-volatility state for Norway's SovCDS (though with weak statistical significance). Interestingly, a rise in commodity prices appears to increase the chance of entering a high-volatility (crisis) state in Russia's SovCDS spreads, consistent with Wegener et al. (2025), who argue that rising oil prices are increasingly seen as risk amplifiers rather than stabilisers for Russia's creditworthiness.

We also perform a robustness check using the quantile regression (QR) method proposed by Koenker and Bassett (1978), which follows a non-linear framework. The QR approach allows for parameter estimates that are robust to outliers to vary across quantiles, effectively capturing asymmetric effects. This methodology is particularly useful for handling skewed and heavy-tailed distributions, as it also captures information at the extremes. The QR approach should assist us in characterising the conditional distribution of

changes in sovereign CDS spreads and offer insights into how they behave under different market conditions. Our QR analysis shows that changes in commodity prices significantly influence fluctuations in sovereign CDS spreads across all quantiles in all countries. Among the countries analysed, Norway's SovCDS spreads show the least responsiveness to commodity market shocks across different quantiles, with Russia's being the most sensitive.

This chapter is especially relevant and timely given the current environment of high debt levels in both developed and emerging economies, along with sharp fluctuations in commodity prices. Our analysis provides investors in commodity-dependent countries with better insights into sovereign debt risks, thereby promoting more informed decisions. Recognising the link between global commodity price swings and sovereign risk is also essential for policymakers, helping them address challenges posed by high sovereign credit risk and commodity price fluctuations. During crises, decision-makers need a clear grasp of the key factors driving sovereign credit risk to make well-informed, effective decisions.

The subsequent sections of this chapter are organised as follows. Section 4.2 reviews the empirical literature on the main determinants of the traditional sovereign. Section 4.3 explains the empirical methodology. Section 4.4 describes the dataset used and introduces the explanatory variables. Section 4.5 presents the main empirical findings along with robustness checks. Finally, Section 4.6 concludes with a discussion of the policy implications.

4.2 Country characteristics, theoretical background, and literature review

4.2.1 Country characteristics

A country is considered dependent on commodity exports if over 60% of its merchandise export value is derived from commodities (UNCTAD, 2023). For Australia, Brazil, Norway, and Russia, commodity exports account for approximately 89%, 73%, 82%, and 78% of their merchandise exports, respectively (UNCTAD, 2023). The report also notes that between 2019 and 2021, commodity exports accounted for about 15% of Australia's GDP, 11% of Brazil's, 22% of Norway's, and 18% of Russia's. It emphasises that Australia mainly exports metals, Brazil focuses on agricultural commodities, and Norway and Russia predominantly export energy commodities.

Marioli and Vasishtha (2025) emphasise that countries relying on commodity exports without sovereign wealth funds or robust fiscal frameworks face significant debt sustainability issues. Some commodity-exporting countries have adopted less pro-cyclical fiscal policies and maintain strong political systems (Mohaddes and Raissi, 2017), which help mitigate debt-related problems (World Bank, 2024). Additionally, Mohaddes and Raissi (2017) find that sovereign wealth funds and enhanced institutional quality can mitigate the adverse effects of unfavourable commodity price shocks.

Norway is recognised for its highly effective fiscal frameworks and institutions for managing its natural resource wealth. Its sovereign wealth fund, the Government Pension Fund Global (GPFG), was established in 1990 to invest oil and gas revenue. As of 2022, DBRS Morningstar reported that the GPFG is the world's largest SWF, with a market value of approximately 348% of mainland GDP at year-end.[24]

The SWF functions as both a stabilisation and savings fund, serving as a fiscal instrument for integrating oil revenues into the Norwegian economy. The GPFG allows the government to adjust fiscal policies in response to fluctuations in petroleum income, offering a substantial buffer against economic shocks.[25]

Norway has implemented fiscal rules to safeguard budgets from fluctuations in commodity prices and economic cycles (Bjørnland and Thorsrud, 2019). Under Norway's fiscal framework, the Government Pension Fund Global (GPFG) receives net cash flows from petroleum activities and is fully invested in global equities, fixed-income securities, and real estate. The fiscal rule requires that countercyclical withdrawals do not exceed the fund's expected real return to maintain its value.[26]

In 2008, Russia created two natural resource funds: the National Wealth Fund and the Reserve Fund. The Reserve Fund, intended as a stabilisation fund to build reserves for covering budget deficits caused by volatile oil and natural gas revenues, was disbanded in 2018 due to depletion from budget deficits and the 2014 oil price collapse (Wood, 2018). The National Wealth Fund (NWF) aims to generate long-term returns to compensate for government losses from sharp declines in oil and gas prices. Since 2014, Russia has also

[24] https://dbrs.morningstar.com/research/412175/dbrs-morningstar-confirms-the-kingdom-of-norway-at-aaa-stable-trend
[25] https://ccsi.columbia.edu/content/managing-public-trust-how-make-natural-resource-funds-work-citizens
[26] https://www.nbim.no/en/news-and-insights/publications/discussion-notes/2023/simulating-trade-offs-in-spending-from-the-government-pension-fund-global/

faced international sanctions. Numerous studies suggest that such sanctions increase the risk of sovereign debt defaults in the targeted countries (see e.g., Apeti and Edoh, 2024).

Brazil set up a non-commodity sovereign wealth fund in 2008 to encourage public savings and cushion against economic fluctuations. However, it was dissolved in 2019 because of the government's substantial external debt. The country experienced a deep recession from 2015 to 2016, exacerbated by declining commodity prices and other factors, including political instability, structural challenges, a high tax burden, and inadequate infrastructure.[27] Although Brazil has introduced fiscal rules, they are often procyclical, creating notable challenges.[28]

Australia's Future Fund, established in 2006, aims to strengthen the government's long-term financial position. Unlike a sovereign wealth fund based on natural resources, it is financed through budget surpluses rather than resource revenues. Although Australia does not have strict fiscal rules like Norway, the government has adopted several fiscal policies to manage the cyclical fluctuations caused by resource booms and busts, helping to stabilise fiscal balances (Garton et al., 2012).

During the period studied, Brazil maintained an investment-grade sovereign credit rating from 2009 until 2016, when it was downgraded to speculative grade (BB). A 2022 DBRS Morningstar press release states that Brazil's low rating is due to its vulnerability to shocks from high public debt and sluggish economic growth.[29] Russia's sovereign debt maintained an investment-grade rating until it was downgraded to speculative grade in 2015. It recovered from 2019 to 2022 but was downgraded again to speculative grade following the invasion of Ukraine and subsequent sanctions.

Both Australia and Norway have maintained investment-grade (AAA) ratings throughout the sample period.[30] Australia's AAA rating is supported by its strengths, such as a diversified, highly productive economy, stable macroeconomic policies, and strong political institutions that help it absorb shocks effectively. Norway's high creditworthiness is due to its SWF, robust institutional framework, and stable political system, all of which help lessen its susceptibility to economic shocks.

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[27] For more details, see https://www.ecb.europa.eu/press/economic-bulletin/html/eb201601.en.html
[28] https://www.elibrary.imf.org/view/journals/002/2023/289/article-A001-en.xml#:~:text=The%20design%20of%20the%20rule,debt%20or%20fostering%20public%20investment.&text=Source:%20Brazil%20National%20Treasury.&text=Source:%20Brazil%20National%20Treasury.,-Public%20Investment&text=Sources:%20FGV%2C%20Observatorio%20de%20Politica%20Fiscal.
[29] https://dbrs.morningstar.com/research/401031/dbrs-morningstar-confirms-brazil-at-bb-low-stable-trend
[30] For more details, see https://www.worldgovernmentbonds.com/world-credit-ratings/

4.2.2 Theoretical background

Commodity price fluctuations influence the terms of trade—the ratio between export and import prices—in small open and commodity-exporting economies. Improving the terms of trade due to rising export commodity prices strengthens sovereign solvency by supporting economic growth, boosting tax revenues, and attracting foreign exchange inflows. This increases the government's capacity to service external debt, easing borrowing constraints, improving access to global financial markets, lowering risk premiums, and narrowing spreads as creditor confidence rises (Hilscher and Nosbusch, 2010; Bastourre et al., 2012; Shousha, 2016).

Conversely, adverse terms-of-trade shocks, such as sudden declines in commodity export prices, reduce export and tax revenues as economic activity slows and labour demand and wages fall. Fewer resources to meet external debt obligations threaten debt sustainability, increasing default risks and widening sovereign yield spreads. The conventional wisdom regards fluctuations in (commodity) terms of trade as a key source of aggregate fluctuations in both developed and developing countries (Mendoza, 1995; Schmitt-Grohé and Uribe, 2018). Generally, more volatile fundamentals imply a higher risk of economic downturns, which can raise default risk and widen bond yield spreads.

The Mundell-Fleming model indicates that a decline in a country's terms of trade often leads to a depreciation of its currency. If a sovereign holds more foreign-currency liabilities than assets, currency depreciation can result in negative wealth effects. Similarly, if the corporate sector's balance sheets have currency mismatches, a currency depreciation reduces collateral value, contracts credit availability, and increases credit costs. Investors perceive these unfavourable financial conditions as likely to slow economic activity and decrease creditworthiness, thereby elevating sovereign default risk (Bernoth and Herwartz, 2021).

The Dutch Disease is a well-documented phenomenon linked to fluctuations in commodity prices (terms of trade). It refers to significant pressures for real exchange rate appreciation due to large capital inflows into booming commodity sectors or surges in commodity revenues (Bastourre et al., 2012; Schedelik et al., 2023). This increases domestic income and spending by the private and public sectors (pro-cyclical fiscal policy), driving inflation and raising output in non-tradable sectors relative to tradable sectors. As a result, real exchange rate appreciation diminishes international competitiveness and impacts long-term growth by reducing manufacturing output. During economic booms, procyclical fiscal

policies can result in unsustainable debt-to-GDP ratios and credit crises, as governments borrow heavily when commodity prices fall, eroding fiscal buffers and missing opportunities to reduce debt during booms. This deterioration in fiscal buffers or external balance weaknesses can cause sovereign rating downgrades and raise SovCDS spreads.

4.2.3 Literature review

4.2.3.1 Background on sovereign credit default swaps

A credit default swap (CDS) is a financial derivative that offers protection against the risk of a reference entity defaulting. The protection seller agrees to compensate the protection buyer if a credit event occurs, in exchange for regular premium payments. The compensation, payable after a credit event affecting the reference entity's debt, is calculated by subtracting the bond's recovery rate from its face value (the notional amount of the CDS).

A sovereign CDS (SovCDS) hedges against financial losses from credit events involving a sovereign reference entity and facilitates trading in sovereign credit risk (IMF, 2013). In an efficient financial market, the CDS spread (or premium) reflects the cost of this protection and indicates the market's perception of a country's creditworthiness. It represents the annual protection cost as a percentage of the notional amount (IMF, 2013). A rising SovCDS spread signals a greater probability of sovereign default. Fluctuations in spreads can be driven by global risk factors, including investor sentiment, export prices, and interest rates, as well as by country-specific factors, such as fiscal health.

A SovCDS and the reference asset offer investors similar exposure to the risks and returns of sovereign debt. In the absence of market friction, the no-arbitrage argument suggests that the CDS spread should roughly match the yield spread of a reference obligation of equal maturity over the risk-free rate (Duffie, 1999). A protection buyer’s exposure is therefore equivalent to a portfolio that combines a long position in a default risk-free bond and a short position in the defaultable bond. Arbitrageurs can capitalise on any price discrepancies between the SovCDS and the underlying sovereign debt by taking offsetting positions.

Some research indicates that the CDS market dominates the bond market in terms of price discovery, meaning it efficiently and promptly reflects new information in prices (Augustin, 2014; Gyntelberg et al., 2018). Blanco et al. (2005) suggest that this is due to the CDS market's synthetic structure, which facilitates easier trading of credit risk. Gündüz and

Kaya (2013) provide evidence that CDS markets are weak-form efficient, quickly integrating information into prices.

Research indicates that information asymmetry among market participants tends to be lower for sovereign credit instruments than for corporate credit risk (Ammer and Cai, 2011). Much of the relevant information about a country's macroeconomic health and government finances is publicly accessible, hence market prices incorporate new information more quickly. Some studies also suggest that the informational efficiency of sovereign Credit Default Swaps (CDS) varies with market conditions (Arce et al., 2013), responding more swiftly to new information during periods of economic instability than the bond market (IMF, 2013).

Unlike corporate debt, sovereign debt does not have a formal bankruptcy process. There is no global legal authority to enforce creditor payments if a sovereign defaults, often leading to disputes over whether a credit event should trigger a Sovereign Credit Default Swap (SovCDS) payout. According to the International Swaps and Derivatives Association (ISDA), qualifying credit events for a SovCDS include fundamental defaults, such as failure to pay interest or principal, and technical defaults, which involve restructuring, repudiation, or debt moratoria (Bomfim, 2023). The ISDA classification is important because countries rarely default outright; instead, they typically restructure or renegotiate their debts (Manzo and Veronesi, 2016). In advanced economies, sovereign CDS spreads more often reflect the likelihood of a technical default rather than a fundamental one.

Duffie et al. (2003) argue that sovereign defaults are mainly political decisions. The possible repercussions of default may deter sovereign debtors from defaulting. Governments weigh the costs of repaying debt against the costs of default, which include reputational damage such as losing access to future borrowing (Eaton and Gersovitz, 1981); disruptions to international trade (Bulow and Rogoff, 1989); negative effects on the domestic economy through the financial system, like decreased foreign investment (Mendoza and Yue, 2012); and political consequences for authorities (Borensztein and Panizza, 2009).

*4.2.3.2 **Modelling sovereign default***

The pricing of corporate credit risk usually relies on either the structural modelling approach developed by Merton (1974) or the reduced-form modelling approach (Duffie, 1999). Merton-type structural models assume that default occurs when a firm’s asset value falls below its contractual debt obligations at maturity, depending on the returns and volatilities of equity and debt. Some research has adapted this model to analyse sovereign defaults. For

example, Gapen et al. (2008) propose that sovereign distress increases when the market value of a country's assets—such as current and future surpluses and international reserves—declines relative to its debt obligations, or when these assets become more volatile.

However, as Manzo and Veronesi (2016) and Doshi et al. (2017) highlight, sovereign default involves more complex dynamics, making it more difficult to identify the key variables that explain sovereign CDS spreads. Government budget data may be unreliable, and default decisions are often influenced by political motives that benefit politicians (Manzo and Veronesi, 2016).

Most studies estimate sovereign CDS prices using a reduced-form approach under the no-arbitrage assumption, reflecting asymmetric information (such as adverse selection and moral hazard) in debt markets (Jarrow, 2011). This arbitrage-free pricing method assumes no market frictions or trade restrictions and considers an equilibrium in the primary debt market amid asymmetric information.

This valuation method uses the risk-neutral present value operator, which determines a security's price as the discounted (at the risk-free rate) expected value of future cash flows. The model defines a default intensity that varies with several state variables, thereby representing the CDS spread as a function of these variables. The CDS premium is set by equating the expected payments to the expected payoff. In Appendix A, we briefly outline a sovereign CDS pricing model based on the work of Doshi et al. (2017) and (2018).

4.2.3.3 Determinants of sovereign credit spreads: Global or country-specific risk factors?

Several researchers have investigated the influence of global and local variables in explaining fluctuations in sovereign credit spreads (Hilscher and Nosbusch, 2010; Longstaff et al., 2011; Augustin, 2018; Doshi et al., 2017). Intuitively, country-specific fundamentals and investors' risk attitudes should influence movements in sovereign CDS spreads (Duffie et al., 2003; Remolona et al., 2008; Hilscher and Nosbusch, 2010).

Aizenman et al. (2016) assess the relative importance of various economic fundamentals in explaining sovereign credit default swap (CDS) spreads in emerging markets from 2004 to 2012. They find that external factors were more important in pricing sovereign risk before the global crisis, while domestic factors became more prominent during and after the crisis. Beirne and Fratzscher (2013) analyse the drivers of sovereign CDS spreads across a group of advanced and emerging economies, showing that SovCDS spreads were more sensitive to fundamentals, which explained a substantially higher share

of movements in sovereign risk during the 2008 to 2011 crisis period than in the pre-crisis period.

Other studies find that sovereign credit risk is primarily influenced by global variables, including financial indicators reflecting global market sentiment and macroeconomic factors (Augustin et al., 2016). Gilchrist et al. (2022) demonstrate that much of the co-movement in sovereign spreads results from shifts in global financial risk. The strong correlation among sovereign spreads can be attributed to the global financial cycle (Miranda-Agrippino and Rey, 2022), which causes synchronised movements in risky-asset prices, capital flows, leverage, and financial indicators worldwide. Doshi et al. (2017) further show that the impact of economic and financial variables on spreads varies considerably over time.

Csonto and Ivaschenko (2013) examine how global and country-specific risk factors influence shifts in emerging market debt spreads. They find that although both sets of factors significantly determine spreads in the long run, global factors have a greater impact in the short term because country-specific fundamentals evolve slowly. Moreover, they observe that countries with stronger fundamentals are less affected by changes in global risk aversion, indicating that robust domestic fundamentals can help shield against shocks in global market sentiment.

Longstaff et al. (2011) demonstrate that changes in sovereign CDS spreads for emerging and developed economies are mainly driven by global risk factors linked to U.S. financial market indicators. Ang and Longstaff (2013) decompose weekly sovereign CDS data from the U.S. and 11 European countries into systemic and country-specific components, showing that systemic sovereign risk is closely related to global financial variables such as stock market returns. Fender et al. (2012), using daily data on emerging market sovereign CDS, find that CDS spreads are more influenced by global and regional risk factors than by country-specific factors, especially during crises. Hibbert and Pavlova (2017) employ quantile panel regressions with daily CDS data from 34 countries and observe that changes in SovCDS spreads are more responsive to financial market conditions than to country-specific variables.

4.2.3.4 Global commodity prices

Reinhart et al. (2016) find that many sovereign defaults, especially in resource-rich countries, often occur after drops in global commodity prices. Several studies emphasise that commodity prices, which influence capital flows—particularly in commodity-dependent

countries—play a crucial role in shaping the global financial cycle (e.g., Miranda-Agrippino and Rey, 2022; Juvenal and Petrella, 2024).

Using daily data from 34 emerging markets, Boehm et al. (2021) provide evidence that higher commodity prices are associated with lower sovereign default risk (measured by the Emerging Market Bond Index yield spread), particularly for countries dependent on commodity exports. Using annual data, Arezki and Brückner (2012) examine the effect of windfall gains from commodity price shocks on sovereign bond spreads using panel data methods. They find that increases in global commodity export prices lead to a significant reduction in sovereign bond spreads in democracies but a significant increase in autocracies. Arezki and Brückner (2012a) observe that rising commodity prices are associated with a reduction in external debt levels, a trend that is significant in democracies but not in autocracies.

Hilscher and Nosbusch (2010) analyse how macroeconomic fundamentals influence emerging market sovereign yield spreads. They discover that fluctuations and volatility in commodity terms of trade, along with global factors such as the VIX, the U.S. spread, the 10-year Treasury yield, and the TED spread, significantly impact credit spreads. Aizenman et al. (2016) find that volatility in commodity terms of trade is positively linked with emerging-market sovereign CDS spreads.

Most existing studies focus on the effect of oil prices on sovereign credit risk. Using a daily dataset, Sharma and Thuraisamy (2013) emphasise the role of oil price uncertainty in predicting sovereign CDS spread returns for eight Asian countries. Duffie et al. (2003) find that Russian yield spreads respond to political events and are negatively related to the country's foreign-currency reserves and oil prices. Stolbov (2017) finds a significant effect of oil prices and the VIX on Russian sovereign CDS spreads at a monthly frequency.

Chuffart and Hooper (2019) examine how oil price returns affect the sovereign CDS spreads of Russia and Venezuela. Using daily spreads and a Time-Varying Transition Probabilities Markov Switching model, they find that crude oil prices and their volatility are key factors influencing sovereign debt, with both global and local factors significantly influencing sovereign CDS spreads. Naifar et al. (2020) utilise quantile regression and causality-in-quantile methods to demonstrate that oil price returns significantly and positively reduce the sovereign credit risk premium for Venezuela, Mexico, and Russia. In contrast, countries with sovereign wealth funds—such as Saudi Arabia, the UAE, and Norway—are relatively insulated. Utilising a bivariate GARCH model, Wegener et al.

(2016) consider nine emerging and advanced countries and find evidence that positive oil price shocks lower sovereign CDS spreads and enhance the fiscal stability of oil-producing countries.

An increase in commodity prices is expected to boost the incomes of resource-rich countries, improving their capacity to meet debt payments. As global investor confidence and market sentiment improve, the risk premium investors require for sovereign default risk should decrease, leading to lower SovCDS spreads. The initial hypothesis we examine is:

Hypothesis 1: Commodity price returns are negatively related to changes in sovereign CDS spreads.

4.2.3.5 ***State dependency***

The literature suggests that sovereign risk pricing may display nonlinear characteristics, indicating that the determinants of CDS spreads vary with the state of the macroeconomy (Augustin, 2014). Recent empirical evidence supports the idea of a regime shift in sovereign debt pricing (Arghyrou and Kontonikas, 2012), demonstrating that CDS spreads behave quite differently during crisis periods compared to more stable times (Fender et al., 2012; Blommestein et al., 2016; Delatte et al., 2017).

Delatte et al. (2017) argue that the risk pricing of financial assets is fundamentally state-dependent, so price-determination models that work well in calm times may be misleading during turbulent periods. Research by Caceres et al. (2010) shows that during the early stages of the Global Financial Crisis (GFC), an increase in global risk aversion significantly widened euro area sovereign spreads. However, as the crisis developed, country-specific factors began to play a prominent role. Doshi et al. (2017) note that the impact of economic and financial variables on spreads varies considerably across countries and over time. The estimated risk premiums are notably time-varying, peaking during the 2008 GFC and the Eurozone debt crisis.

The IMF (2013) indicates that SovCDS spreads respond more quickly to new information during stressful periods than in calmer times. Boehm et al. (2021) examine the link between commodity and sovereign risk and find that dependence on commodity prices increases during economic downturns when fiscal capacity is limited. Consequently, market participants in sovereign CDS tend to pay more attention to commodity price shocks during crises, especially when economic fundamentals weaken, and sovereign debt issuance rises. Building on this, we also test the following hypothesis:

Hypothesis 2: The effect of changes in global commodity prices on sovereign CDS spreads is state-dependent and especially pronounced during turbulent periods.

4.3 Econometric methodology

To establish a baseline, we initially estimate a linear regression model for each sovereign CDS spread change, formulated as follows:

$$y_t = \alpha + X_t'\beta + \varepsilon_t \tag{4.1}$$

where y_t is the dependent variable, X_t is the vector of regressors, which includes lagged values of the dependent variable and the error term $\varepsilon_t \sim i.i.d.N(0, \sigma^2)$. The OLS regressions assume that ε_t is independent of x_t. We follow previous studies in running the regression on first-differenced data (e.g., Blommestein et al., 2016; Chuffart and Hooper, 2019).

4.3.1 Markov-switching Dynamic Regression Model

To capture the time-varying nature of the relationship between commodity price changes and SovCDS spreads, we specify a Markov-switching model. A Markov-switching model for equation (4.1) is specified as follows:

$$y_t = \alpha_{S_t} + X_t'\beta_{S_t} + \sigma_{S_t} z_t \quad S_t = \{1, 2\} \tag{4.2}$$

where X_t is a vector of regressors and $\sigma_{S_t} z_t = \varepsilon_t$ with $z_t \sim i.i.d.N(0, 1)$. The terms α_{S_t} and σ_{S_t} are, respectively, the regime-dependent intercept and variance of the target variable y_t, while β_{S_t} is a vector of state-dependent coefficients for the regressors. S_t is an unobservable state variable, which is independent of z_t.

In line with previous research (e.g., Blommestein et al., 2016; Chuffart and Hooper, 2019), the variation in the sovereign CDS spread is influenced by two unobservable regimes, $S_t = \{1, 2\}$, corresponding to a turbulent (crisis or high-volatility) regime and a tranquil (non-crisis, calm or low-volatility) regime. The state variable is assumed to be generated by a discrete-state, homogeneous, irreducible, and ergodic Markov chain (MC) such that:

$$Pr(S_t = j | S_{t-1} = i, S_{t-2} = k, \dots, \Delta x_t') = Pr(S_t = j | S_{t-1} = i) = p_{ij}, \tag{4.3}$$

where p_{ij} is the probability that, starting in the regime i, the model may move to the regime j. The transition matrix for the two-state case is thus represented by

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \tag{4.4}$$

where $p_{11} + p_{12} = 1$ and $p_{21} + p_{22} = 1$.

With latent states, the conditional density of y_t is given by $f(y_t|s_t = i, \mathcal{F}_{t-1}; \theta)$ for $i = 1,2$. The marginal density of y_t is obtained by weighting the conditional densities by their respective probabilities; that is:

$$f(y_t|\theta) = \sum_{i=1}^{2} f(y_t|S_t = i, \mathcal{F}_{t-1}; \theta) \Pr(S_t = i; \theta) \tag{4.5}$$

where $\mathcal{F}_{t-1}$ is all the past information up to time $t-1$ and θ is the vector of model parameters to be estimated.

Because the regimes are unobservable, to construct the likelihood function, we make inferences about the probability that S_t takes on a specific value based on what we observe at time t and the population parameters θ, that is, $\xi_{i,t} = \Pr(s_t = i|\mathcal{F}_{t-1}; \theta)$. These are the filtered regime probabilities because they are based on real-time information $\mathcal{F}_{t-1}$. Since the state can either be 1 or 2, $\xi_{1,t} + \xi_{2,t} = 1$. Then,

$$\Pr(s_t = i|\mathcal{F}_t; \theta) = \frac{f(y_t|s_t = i, \mathcal{F}_{t-1}; \theta) \Pr(s_t = i|\mathcal{F}_{t-1}; \theta)}{f(y_t|\mathcal{F}_{t-1}; \theta)} \tag{4.6}$$

where $f(y_t|\mathcal{F}_{t-1}; \theta)$ is the likelihood of y_t and $\Pr(s_t = i|\mathcal{F}_{t-1}; \theta)$ is the probability of $S_t = i$ given observation until time $t-1$. Under the Gaussian assumption of the error terms, we have the conditional densities

$$\eta_{i,t} = f(y_t|s_t = i; \mathcal{F}_{t-1}; \theta) = \frac{1}{\sqrt{2\pi\sigma_i}} exp\left[-\frac{(y_t - \alpha_{S_t} - x_t'\beta_{S_t})^2}{2\sigma_j^2}\right] \quad \text{for } i = 1,2. \tag{4.7}$$

where the conditional density of the observation is thus the probability-weighted sum of both states, given by

$$f(y_t|\mathcal{F}_{t-1}; \theta) = \sum_{i=1}^{2}\sum_{j=1}^{2} p_{ij}\xi_{1,t-1}\,\eta_{i,t} \tag{4.8}$$

and the log-likelihood function associated with the iteration is

$$L(\theta) = \sum_{t=1}^{T} log\ f(y_t|\mathcal{F}_{t-1}; \theta) = \sum_{t=1}^{T} log\left(\sum_{i=1}^{2}\sum_{j=1}^{2} p_{ij}\xi_{1,t-1}\,\eta_{i,t}\right). \tag{4.9}$$

The model parameters can be estimated by maximising the log-likelihood function $L(\theta)$.

4.4 Data

4.4.1 The dependent variable: the sovereign CDS spread

We examine how fluctuations in commodity prices affect a country's sovereign creditworthiness. The dependent variable in our regressions is the weekly change in the logarithm of the 5-year dollar-denominated sovereign CDS spread, which is typically the most liquid maturity for CDS contracts. We obtain daily mid-market SovCDS spread quotes from DataStream, covering the period from 22 December 2008 to 18 February 2022, just before the onset of the Russo-Ukrainian War. To minimise measurement errors that could impact daily spreads, we use weekly data calculated by averaging the daily data (ending on Friday).[31]

Figure 4.1 shows a time-series plot of sovereign Credit Default Swap (CDS) spreads (in logarithmic terms) for the selected countries. There is a notable increase in sovereign CDS spreads during the Eurozone debt crisis in 2011 and 2012, the collapse in commodity prices from 2014 to 2016, and the COVID-19 pandemic. The SovCDS spreads of emerging economies reached peaks in 2015 that were higher than those recorded during both the Eurozone debt crisis and the COVID-19 pandemic. Notably, the sovereign CDS spreads for Australia and Norway have been declining since the highs reached during the Eurozone crisis.

4.4.2 Global Commodity Price Changes

We use the S&P Goldman Sachs Commodity Index (GSCI) Total Return Index as a proxy for the global commodity market. The GSCI is a production-weighted index of the prices of exchange-traded, liquid, and physically settled commodity futures contracts across sectors, including energy, agricultural products, and metals. It is a tradable index offering broad exposure to the commodities market (see Rallis et al., 2013). It is generally regarded as a barometer of global economic trends, as economic and geopolitical conditions influence commodity prices.

Weekly index returns are the logarithmic changes of the weekly (average of daily data) S&P GSCI index, calculated as follows:

[31] Table 4.1 outlines the data sources.

$$\Delta COMM_t = ln\left({GSCI_t^w}/{GSCI_{t-1}^w}\right) \quad (4.10)$$

where w denotes weekly.

4.4.3 Control variables

Building on previous studies in the literature using high-frequency data, we include the following global and domestic risk factors as control variables.

4.4.3.1 Domestic variables

Local stock market returns (*SR*). A stock market index is a useful leading indicator of economic activity and a barometer of investor sentiment. If investors are rational and forward-looking, stock market movements should reflect changing expectations of future earnings and, hence, of economic growth (Stock and Watson, 1989; Shiller, 2003). Rising stock market returns signal strong economic growth and positive investor sentiment, both of which are associated with lower sovereign default risk (Chiarella et al., 2015). We expect that changes in SovCDS spreads are negatively and significantly related to domestic stock market fluctuations.

Foreign exchange returns (FX). The traditional Mundell-Fleming model suggests that a currency depreciation worsens a country's terms of trade by lowering the foreign-currency price of exports, thereby increasing net exports and enhancing competitiveness. An increase in aggregate output can help reduce sovereign risk pressures (Basher et al., 2016; Bernoth and Herwartz, 2021). However, with external debt, a substantial currency depreciation can also raise the debt burden, potentially leading to sovereign defaults (Asonuma, 2016). Additionally, currency depreciation may weaken corporate balance sheets, raise risk premiums, and deteriorate financial conditions, possibly slowing economic activity (Bernoth and Herwartz, 2021). International investors might interpret this as a decline in sovereign creditworthiness, resulting in wider sovereign yield spreads (e.g., Bernoth and Herwartz, 2021). Therefore, we expect currency depreciation to increase sovereign CDS spreads when the 'financial channel' dominates.

4.4.3.2 Global variables

Global stock market return (SP500). We use the S&P 500 total return index as an indicator of global economic activity. As the largest economy, the U.S. has a significant influence on the global economy, and data shows that disruptions in U.S. financial markets affect markets worldwide. Therefore, U.S. security prices are seen as valuable signals of economic

fundamentals or of market liquidity that affect international assets (e.g., Longstaff et al., 2011). We expect S&P 500 returns to be negatively correlated with sovereign CDS spreads.

VIX index.[32] The Chicago Board Options Exchange Volatility Index (VIX) is often used as a proxy for global investor sentiment and market volatility (Bekaert and Hoerova, 2014). A higher VIX, which indicates greater risk aversion, is expected to widen sovereign CDS spreads (see Pan and Singleton, 2008; Hilscher and Nosbusch, 2010).

U.S. 5-year Treasury yield. This variable aims to capture expectations of US and global macroeconomic conditions (Longstaff et al., 2011). Since interest rates generally correlate positively with economic growth, a negative relationship between the 5-year Treasury rate and SovCDS spreads is expected.

TED spread (TED). The TED spread is the difference between the 3-month USD LIBOR and the 3-month US T-bill yield, which tends to spike during periods of crisis. Fluctuations in the TED spread reflect changes in global credit and liquidity risks (Hilscher and Nosbusch, 2010). Therefore, it is commonly used as an indicator of funding liquidity. We expect that the higher the TED spread, the higher the risk of default, thus widening sovereign CDS spreads.

MOVE index (MOVE).[33] The 1-month Merrill Lynch Option Volatility Estimate (MOVE) index reflects global bond market uncertainty and investors' risk aversion. The MOVE index indicates changes in risk within fixed-income markets and serves as a proxy for global bond market sentiment (Fender et al., 2012). Investors may require higher compensation to hold sovereign bonds when market uncertainty and risk aversion increase.

4.4.4 Preliminary data analyses

Table 4.2 shows the summary statistics of weekly changes in the time series data. All data series, except the US 5-Year Constant Maturity and the TED spread, are first log-transformed and then differenced.

Among the sampled countries, Russia (Norway) has the largest (smallest) maximum change in the SovCDS spread. Australia's SovCDS spread changes have the smallest mean,

[32] The VIX index is the "risk-neutral" expected stock market variance for the US S&P500 contract over the next 30 days and is computed from a panel of options prices (Bekaert and Hoerova, 2014). The VIX is quoted in percentages.

[33] The MOVE index is a weighted average of implied volatilities of one-month at-the-money OTC Treasury options written on benchmark Treasury securities with maturity periods of 2 years, 5 years, 10 years and 30 years (Zhou, 2014). It is expressed in basis points.

followed by Norway. The standard deviation of SovCDS spread changes is lowest (highest) for Norway (Russia), reflecting the country's more stable (volatile) economic, fiscal, and political environment, signalling lower default risk. The statistics indicate that the distribution of changes in the SovCDS spread is asymmetric and leptokurtic, suggesting heavy tails or outliers. The Jarque-Bera statistics confirm that the normality hypothesis is rejected for all datasets.

Table 4.3 reports the correlations among the explanatory variables. Clearly, financial variables are highly correlated, and including all of them in a regression can result in multicollinearity, which may affect identification. The change in the GSCI index ($\Delta COMM$) variable is also strongly correlated with several other explanatory variables, including stock and foreign-exchange returns. A regression using the correlated data likely yields a coefficient on $\Delta COMM$ that does not fully capture the effect of commodity price exposure on sovereign CDS spreads, since other correlated regressors also partly reflect the influence of commodity price fluctuations (Umar et al., 2018).

To evaluate the maximum impact of exposure to global commodity price fluctuations, we therefore conduct our regression analyses using local variables and US stock returns that are orthogonalised (see, e.g., Blommestein et al., 2016; Bekaert et al., 2016; Umar et al., 2018). Orthogonalisation aims to remove the effects of other highly correlated regressors from the global commodity price change variable.

Following Blommestein et al. (2016), the orthogonalized variable is defined as the sum of the estimated intercept and the residuals from regressing the raw variable on other correlated regressors. For the domestic stock market, foreign exchange, and the S&P 500 return variables, we estimate the following auxiliary regressions:

$$SR_t = \alpha^{SR} + \beta_1 \Delta COMM_t + \beta_2 \Delta SP500_t + \beta_3 \Delta FX_t + \nu_t^{SR} \quad (4.11a)$$

$$\Delta FX_t = \alpha^{FX} + \beta_1 \Delta COMM_t + \beta_2 \Delta SP500_t + \nu_t^{FX} \quad (4.11b)$$

$$\Delta SP500_t = \alpha^{SP500} + \beta_1 \Delta COMM_t + \beta_2 \Delta VIX_t + \nu_t^{SP500} \quad (4.11c)$$

$$\Delta VIX_t = \alpha^{VIX} + \beta_1 \Delta COMM_t + \nu_t^{VIX} \quad (4.11d)$$

where the ν_t^{SR}, ν_t^{FX}, ν_t^{SP500}, and ν_t^{VIX} denote the residual parts which, by construction, are uncorrelated with movements in the correlated regressors.[34] The orthogonalized variable

[34] Please note that for Brazil, to tame multicollinearity, we also include changes in the TED spread as a regressor when orthogonalizing the domestic stock market returns.

employed in our main analyses as an explanatory variable is given by the sum of the estimated intercept α^i and the residual v_t^i where $i = \{SR, \Delta FX, SP500, \Delta VIX\}$.

A regression using the orthogonalized variables should therefore enable the commodity price change coefficient to capture all covariances with these other factors (Bekaert et al., 2016), thus reducing potential multicollinearity issues and enhancing identification.

4.5 Empirical results and discussion

4.5.1 OLS regression analysis

We start with least-squares regressions of changes in the SovCDS spread against changes in commodity prices and a set of control variables. The linear OLS regression model specification is as follows:

$$\Delta SovCDS_t = \alpha + \sum_{i=1}^{3} \beta_i \Delta SovCDS_{t-i} + \gamma \Delta COMM_t + \Delta X_t' \delta + \varepsilon_t, \qquad (4.12)$$

where $\Delta SovCDS_t$ is the logarithmic change in the SovCDS spread, $\Delta COMM_t$ is the logarithmic change in the GSCI index, and X_t denotes the vector of country-specific and global factors. To capture the persistence of changes in SovCDS spreads, the regression includes autoregressive terms up to the third order (see Arghyrou and Kontonikas, 2012; Riedel et al., 2013).[35]

Table 4.4 presents the results of the estimated linear regression model. As expected, the ΔCOMM coefficients are negative and statistically significant at the 1% level across all countries. Higher commodity prices increase export revenues and fiscal income in commodity-exporting nations, thereby improving debt sustainability and, consequently, boosting investor confidence. An increase in commodity prices should therefore lead to a reduction in sovereign CDS spreads, as investors demand lower risk premiums.

Typically, commodity price shocks are expected to have a stronger impact on emerging-market SovCDS spreads than on those in advanced economies. This is mainly because advanced economies tend to have more diversified industries, stronger regulatory

[35] We initially specified the model with one lag of the dependent variable to account for persistence; however, diagnostics (Q-statistics) indicate remaining autocorrelation in standardised residuals. Hence, three autoregressive terms, also supported by the BIC criterion, are included to mitigate for residual autocorrelation in the estimation.

frameworks, political stability, and larger fiscal buffers. These factors are crucial for investors, boosting confidence and, as a result, reducing the risk premiums they require. Our results show that the ΔCOMM coefficients for Brazil (-1.162) and Russia (-1.363) are larger in magnitude than those for Australia (-0.821) and Norway (-0.435).

The local stock market is regarded as a variable that offers forward-looking insights into the economy and is therefore seen as an indicator of the domestic business cycle (Fischer and Merton, 1984). It is also viewed as reflecting a country's debt capacity. We observe a statistically significant negative relationship between domestic stock market returns and changes in SovCDS spreads in Australia, Brazil, and Russia, but not for Norway.

Our findings indicate that when local currencies depreciate against the dollar (i.e., an increase in ΔFX), the cost of protection against default risk rises notably across all countries studied, except Norway. This implies that the financial (balance sheet) transmission mechanism has a greater role in transmitting exchange rate shocks than the net trade channel in Australia, Brazil, and Russia. The estimated effects of exchange rate fluctuations are more pronounced in emerging markets than in advanced economies. Emerging economies often carry a larger proportion of external debt, which can render them more susceptible to foreign-currency fluctuations. As a result, a strong and appreciating US dollar complicates management of external debt, especially for emerging market economies.

An increase in global equity returns, proxied by the S&P 500, significantly reduces SovCDS spreads across all countries. This shows that strong performance in the U.S. stock market, which also reflects positive investor sentiment, generally benefits global sovereign credit markets (Fender et al., 2012). Conversely, a rise in the VIX index signals increased global financial uncertainty. Consistent with economic theory, sharp increases in the VIX are associated with a significant widening of sovereign CDS spreads in all countries examined (Longstaff et al., 2011; Pan and Singleton, 2008).

Fluctuations in the TED spread significantly and positively influence the sovereign creditworthiness of only Brazil and Norway. The positive coefficient supports the hypothesis that a higher TED spread, which signals increased global liquidity risk, is linked to higher sovereign credit risk. Changes in the MOVE index also tend to increase SovCDS spreads. This relationship is statistically significant at the 5% level in Brazil but only marginally in Australia. In contrast, variations in the U.S. 5-Year Treasury rate do not have a significant impact across these countries. The SovCDS spread regressions for Brazil and Russia have

higher adjusted R^2 values (around 60%) compared to those for developed economies (approximately 44% for Australia and about 19% for Norway).

A key concern in our analysis is endogeneity, which can arise from fluctuations in sovereign CDS that influence investors' expectations of domestic macroeconomic fundamentals. Variations in SovCDS markets directly impact a country's borrowing costs (Delatte et al., 2017), which, in turn, can significantly affect the domestic economy and asset prices (Blommestein et al., 2016). Consequently, sovereign CDS spreads may have feedback effects on the domestic factors we examine. Ignoring potential endogeneity can lead to biased estimates. To explore possible endogeneity, we performed additional single-regime regression analyses. We instrumented the local determinants of the SovCDS spread (i.e., SR and ΔFX) using their lagged values, as historical data are unaffected by future changes. Since our model includes the third lag of ΔSovCDS as an explanatory variable, we used the fifth and sixth lags of SR and ΔFX as relevant instruments (see Qian et al., 2017). The Durbin, Wu, and Hausman Lagrange Multiplier tests for exogeneity did not reject the assumption of exogeneity in any of the four countries, suggesting insufficient statistical evidence for endogeneity severe enough to bias the estimates.

4.5.2 The constant transition probability Markov-switching model

In this section, we employ a two-state Markov regime-switching dynamic regression framework to examine whether the effect of global commodity prices on sovereign CDS spreads in commodity-export-dependent countries is regime-dependent. Tables 4.5 and 4.6 display summarised estimation results for the following Markov regime-switching model:

$$\Delta SCDS_t = \alpha_{S_t} + \sum_{i=1}^{3} \beta_{i,S_t} \Delta SCDS_{t-i} + \gamma_{S_t} \Delta COMM_t + \Delta X_t' \delta_{S_t} + \varepsilon_t \qquad (4.13)$$

where $\varepsilon_t \sim N(0, \sigma_{S_t}^2)$ and $S_t = 1,2$.

The Ljung-Box Q (LBQ) test statistic is used to determine whether the standardised residuals and squared standardised residuals are independent. Standard errors derived from the Huber-White sandwich estimator are applied to correct for heteroscedasticity if the null hypothesis that the autocorrelations of squared standardised residuals up to lag *k* equal zero is rejected.

We examine variance inflation factors (VIF) to assess whether multicollinearity among the regressors affects the accuracy of our estimates. According to the literature, the VIF value for a coefficient should not exceed 10. We find that the VIF values are generally

below 5, indicating that multicollinearity does not substantially affect our regressions. The Durbin-Watson statistic, ranging from 1.9 to 2.1, indicates no significant autocorrelation in the data.

We calculate the regime classification measure (RCM) to evaluate the precision and fit of the Markov-switching model (see Ang and Bekaert 2002).[36] Tables 4.5a and 4.5b show that all RCM statistics fall below 50. Specifically, Australia, Norway, and Russia have RCM values of 33, 31, and 24, respectively, while Brazil's RCM is notably higher at 48. These figures suggest that the model effectively distinguishes between regimes at each point (see Chan et al., 2011).

The reported SIGMA value is an estimate of the regime-dependent standard deviation, with two identified regimes characterised by low and high volatility. The low-volatility state is regarded as a calm, non-crisis regime, while the high-volatility state is seen as a turbulent, crisis regime. Our estimates indicate that SovCDS spread volatility varies considerably between these two states, highlighting regime differences and evidence of transitions between high- and low-volatility states. Notably, in Australia and Norway, volatility during turbulent periods is around 2.5 and 6 times greater than during tranquil periods, respectively. In contrast, in Brazil and Russia, crisis regime volatility is approximately 1.5 and 1.3 times higher, respectively.

The analysis shows that high global commodity prices are associated with statistically significant (1% level) decreases in sovereign CDS spreads across Australia, Brazil, and Russia in both stable and turbulent regimes. However, in the case of Norway, this effect is not significant during the non-crisis period, despite the strong significance indicated by the OLS results. This suggests that a decline in commodity prices is unlikely to substantially impact Norway's sovereign CDS spreads during peaceful times, unlike in Australia, Brazil, and Russia.

Furthermore, the estimated ΔCOMM coefficients are notably higher in turbulent states compared to tranquil regimes across all countries. This supports the empirical findings that SovCDS markets are more sensitive to fundamentals during periods of high volatility (Beirne and Fratzscher, 2013). Fender et al. (2012) find that investors tend to become more

[36] $RCM = \frac{400}{T}\sum_{t=1}^{T} p_t(1-p_t)$ where p_t is the smoothed regime probability $p(S_t = 1|\mathcal{F}_t)$. The RCM ranges between 0 and 100, where 0 indicates that the Markov-Switching model perfectly classifies regimes and 100 indicates the model's failure to classify regimes. Hence, lower values denote better regime classification.

vigilant in assessing risks during crisis periods, mainly adjusting their portfolios in response to global developments.

Russia's SovCDS spread, followed by Brazil, shows the highest sensitivity to changes in global commodity prices, while Norway displays the least sensitivity in both regimes. Both Australia and Norway hold AAA SovCDS ratings. Norway has a commodity-funded sovereign wealth fund, whereas Australia maintains a non-commodity sovereign wealth fund. Norway's SWF, the largest in the world, acts as a buffer against global shocks such as oil price fluctuations. Its high creditworthiness is supported by an efficient financial sector, prudent fiscal policies, low public debt, and stable political institutions within a secure environment. During the period analysed, Russia faced sanctions and increased geopolitical risks, which likely weakened its economic and business environment, making it more susceptible to global shocks. In recent years, Brazil's fiscal vulnerabilities (e.g., high debt levels, rising interest payments) have increased, and economic growth has slowed, impairing market confidence and heightening sensitivity to shocks.

The estimated coefficient on the first lag of ΔSovCDS is positive and statistically significant across both regimes for the developed economies (Australia and Norway). It is significant only in the tranquil regime for Brazil and Russia. The coefficient on $\Delta SovCDS_{t-2}$ is significantly negative in the turbulent regimes for Brazil and Norway, and in the tranquil state for Russia. The third lag, $\Delta SovCDS_{t-3}$, is significantly positive in the tranquil regimes of Brazil and Norway.

The domestic factors (ΔFX and SR) are estimated to have limited effects on Australia's and Norway's SovCDS, while their effects are highly significant across both regimes for Russia. Chuffart and Hooper (2019) note that currency depreciation mainly increases Russia's sovereign CDS spreads during tranquil periods. The coefficients on ΔSP500 and ΔVIX are highly statistically significant across both regimes for Australia, Brazil, and Russia, but only during the crisis regime for Norway.

The ΔMOVE coefficients are only significant during the tranquil regimes for Australia and the turbulent regimes for Brazil. The effect of ΔTED is significant in both regimes for Norway, but only in the turbulent regime for Brazil and Russia. Our results confirm that changes in the 5-year Treasury rate have no significant effect on changes in SovCDS spreads across all sampled countries.

The probability of remaining in the low-volatility regime is about 0.93 for Australia, 0.91 for Brazil, and 0.97 for Russia. Conversely, the likelihood of staying in the turbulent

regime is approximately 0.8 for Australia and 0.9 for both Brazil and Russia. The implied expected durations reveal that the low-volatility regime lasts around 14 and 34 weeks for Australia and Russia, while the high-volatility (turbulent) regime persists for roughly 5 and 12 weeks, respectively. This aligns with the observation that crisis periods generally have a shorter duration than non-crisis periods (Basher et al., 2018). For Brazil's sovereign CDS spread, the tranquil and crisis regimes tend to last about 11 and 10 weeks, respectively, possibly reflecting Brazil's prolonged economic recession from 2014 to 2022. However, for Norway, the transition probabilities are somewhat low, with the probability of remaining in the low-volatility state (around 0.77) being lower than that of remaining in the volatile regime (0.8). Similarly, the implied expected durations in the calm and crisis states are approximately 4 and 5 weeks, suggesting more frequent shifts between volatility regimes.

Figure 4.2 displays the smoothed probabilities of the high-volatility state for each country. These probabilities are vital for understanding regime-switching behaviour in relation to changes in CDS spreads and for pinpointing the timing and occurrence of regime shifts. The transition probabilities indicate that low-volatility (calm) states were especially persistent for Russia's CDS spreads, particularly between 2014 and the start of the COVID-19 pandemic, when a crisis regime emerged. In contrast, consistent with the low persistence of the states demonstrated by the transition probabilities and the expected durations in Table 4.5b, Norway's smoothed probability series fluctuates erratically between crisis and non-crisis states, especially from January 2013 to March 2021.[37] However, despite the erratic transitions, the estimated volatilities and coefficients reported in Table 4.5b differ significantly across regimes, suggesting that the model meaningfully distinguishes between structurally different low- and high-volatility market regimes.

To assess whether commodity index returns and control variables exert asymmetric influences on fluctuations in the SovCDS spread, we perform a Wald-type test for coefficient equality between tranquil and turbulent periods. Table 4.7 displays the test statistics, which follow a Chi-square distribution, along with their p-values. The null hypothesis states that the coefficients are equal across the two regimes, indicating symmetry; the alternative suggests differences. Rejecting the null indicates the presence of asymmetric effects on changes in the SovCDS spread.

[37] The erratic fluctuations in the smoothed probabilities likely stem from model misspecification or high noise. To address this, we experimented with various initial values, including higher randomised starting values, but without success. Removing insignificant variables from the models also did not improve the situation. We additionally explored the time-varying transition probabilities (TVTP) Markov-switching dynamic regression approach, which will be discussed in the next section.

The evidence indicates asymmetric effects of commodity index changes on SovCDS spreads in Brazil and Norway at the 1% significance level, and in Russia at the 10% level. For Australia and Norway, significant asymmetric effects (at the 1% level) are observed for the variables SP500 returns and VIX changes. In Brazil, both foreign and local stock market returns have asymmetric impacts on changes in SovCDS spreads. In Russia's case, all the control variables (except ΔMOVE) exhibit asymmetric effects on the SovCDS spread. Finally, the null hypothesis of symmetric coefficients for SIGMA is rejected in Australia, Brazil, and Norway, suggesting that volatility in changes of sovereign CDS spreads varies substantially across the two states.

4.5.3 **Robustness checks**

In this section, we perform robustness checks to validate the stability and reliability of our findings.

4.5.3.1 Evidence from Time-varying Transition Probabilities

In the previous section, the Markov chain process is time-homogeneous, meaning the probability of switching between regimes remains constant over time. This fixed transition-probability (FTP) restriction excludes the possibility that certain variables or indicators might contain information about the likelihood of switching between different regimes. Markov-switching models with time-varying transition probabilities (Filardo, 1994) address this limitation by allowing these probabilities to vary with exogenous or predetermined variables.

In this section, we employ the time-varying transition probability (TVTP) framework to assess evidence of commodity price asymmetry, allowing the transition probabilities that govern the regime-switching process to depend on specific variables. Specifically, we examine whether changes in global financial stress and/or commodity prices affect the likelihood of switching between low-volatility (calm) and high-volatility (crisis) regimes, or the probability of remaining in a particular regime.

We examine whether changes in the S&P GSCI commodity index, $\Delta COMM_{t-1}$, influence transition probabilities. Commodity prices play a crucial role in determining a country's terms of trade, which are known to impact sovereign risk (Hilscher and Nosbusch, 2010). Higher commodity prices increase the sovereign's resources to service its debt, reducing the likelihood of default and lowering sovereign spreads, thereby boosting investor confidence. An adverse shock may lead investors to reevaluate their positions, increasing

sovereign CDS trading activity and market volatility. Boehm et al. (2021) note that investors pay more attention when commodity prices fluctuate sharply, expecting higher sovereign risk if the prices of a country's exported commodities fall. We expect the previous period's commodity prices to significantly influence the behaviour of sovereign CDS market participants.[38]

The Office of Financial Research (OFR) Financial Stress Index (FSI) is a daily indicator of stress in global financial markets. It is derived from 33 financial market variables and captures stress contributions from both advanced economies and emerging markets (Monin, 2019). Financial stress can impair markets' capacity to fund sovereign liabilities, resulting in diminished risk appetite and decreased market liquidity (Rho and Saenz, 2021). Investors tend to scrutinise the fundamentals that influence a country's default risk more closely during periods of stress. The IMF (2013) notes that SovCDS generally respond more swiftly to shocks under stress conditions, with a markedly higher volume of sovereign CDS trades during such periods. Caceres et al. (2010) observe that increased global risk aversion during the GFC led to a significant widening of euro area sovereign spreads.

We extend our two-state Markov regime switching model in equation (4.2) by allowing the transition probabilities to vary over time, with the following transition matrix:

$$P(t) = \begin{bmatrix} p_{11,t}(Z_{t-1}) & 1 - p_{11,t}(Z_{t-1}) \\ 1 - p_{22,t}(Z_{t-1}) & p_{22,t}(Z_{t-1}) \end{bmatrix}, \tag{4.14}$$

where $Z_{t-1} = [\Delta lnCOMM_{t-1}, \Delta FSI_{t-1}]$. ΔFSI is a change in the weekly average of the OFR FSI. Notice that $p_{ii,t}(Z_{t-1})$ is the probability of staying in the regime i, and $p_{ij,t}(Z_{t-1}) = 1 - p_{ii,t}(Z_{t-1})$ is the probability of switching from regime i to j where $i, j = 1,2$. Using the logistic functional form, the time-varying transition probabilities are defined as follows:

$$p_{11,t}(Z_{t-1}) = \frac{exp(\alpha_1 + \beta_1 \Delta lnCOMM_{t-1} + \gamma_1 \Delta FSI_{t-1})}{1 + exp(\alpha_1 + \beta_1 \Delta lnCOMM_{t-1} + \gamma_1 \Delta FSI_{t-1})} \tag{4.15a}$$

$$p_{22,t}(Z_{t-1}) = \frac{exp(\alpha_2 + \beta_2 \Delta lnCOMM_{t-1} + \gamma_2 \Delta FSI_{t-1})}{1 + exp(\alpha_2 + \beta_2 \Delta lnCOMM_{t-1} + \gamma_2 \Delta FSI_{t-1})}. \tag{4.15b}$$

Statistically significant coefficient estimates for $(\beta_1, \beta_2, \gamma_1, \gamma_2)$ indicate the importance of Z_{t-1} variables in explaining shifts between the two regimes. The signs of the coefficient

[38] We also tested several other candidate transition variables that might influence the likelihood of switching between the two regimes, such as the VIX, the CBOE Crude Oil Volatility Index (OVX), and the 10-Year Treasury Constant Maturity minus 2-Year Treasury Constant Maturity spread. Alternative financial stress indicators (e.g., the St. Louis Fed Financial Stress Index (STLFSI) and the Kansas City Financial Stress Index (KCFSI) were also considered.

estimates govern the dynamics of regime switching. If $\beta_1, \gamma_1 > 0$, then, on average, a positive change in Z_{t-1} raises the probability of remaining in regime 1. Similarly, $\beta_2, \gamma_2 > 0$ implies that an increase in Z_{t-1} increases the probability of remaining in the second regime. The parameters α_1 and α_2 determine the transition probability value in the absence of $\Delta COMM$ and ΔFSI effects.

Tables 4.7a and 4.7b show the estimation results for the TVTP Markov-switching regression models. We observe that most results from the TVTP model are qualitatively similar to those of its FTP counterpart. Results confirm that commodity price changes have the least effect on sovereign credit risk in Norway across both calm and crisis regimes. We observe the impact is greatest on Brazil's (Russia's) sovereign risk during crisis (calm) states. The size of the impact during crisis regimes is about twice that estimated in low-volatility states for Australia, Brazil, and Russia, underscoring that relying on a linear model provides an incomplete picture of the factors influencing creditworthiness and can lead to misleading conclusions during crisis periods (Delatte et al., 2017). We also reaffirm the OLS and FTP model results that domestic factors (ΔFX and SR) have no significant effect on changes in Norway's sovereign CDS spread.

Results suggest that fluctuations in commodity prices do not substantially influence the chance of regime shifts in Australian and Brazilian sovereign CDS spreads. The coefficient β_1 is positive and significant (weakly) for Norway, indicating that higher global commodity prices increase the likelihood that Norway's SovCDS stays in the low-volatility regime. Alternatively, it reduces the likelihood of transitioning from a non-crisis to a high-volatility regime. Interestingly, β_1 is negative and statistically significant for Russia's SovCDS spreads, indicating that rising commodity prices decrease the probability of remaining in the low-volatility regime (i.e., increases the likelihood of moving to a high-volatility state).[39] This could be because, during the study period, market participants associated higher commodity prices with conditions that deteriorate Russia's creditworthiness. Sanctions, financial restrictions, and increased geopolitical instability might have altered the usual effects of oil price changes on Russia's sovereign credit, as discussed by Wegener et al. (2025).[40]

[39] A tested-down model which excludes the ΔMOVE and ΔUS5YR terms also yields a similar finding for Russia (not reported but available upon request).

[40] Wegener et al. (2025) explore the predictability of sovereign Credit Default Swap (CDS) spread dynamics, finding for Russia, a clear transition from a negative to a positive predictive coefficient on oil prices. They argue that rising oil prices are now perceived as a risk amplifier rather than a stabilising factor.

The parameter associated with the lagged ΔFSI (γ_1) is negative and statistically significant in Australia, Brazil, and Russia. This suggests that increased global financial stress reduces the likelihood of staying in a low-volatility state. Essentially, stress periods raise the chances of transitioning from a calm to a turbulent regime. Conversely, in Norway, ΔFSI generally does not affect the probability of regime change, suggesting a higher resilience to financial stress shocks.

The RCM values reported in Tables 4.7a and 4.7b indicate that $\Delta COMM_{t-1}$ and ΔFSI_{t-1} capture the regime classification well in the sampled countries. The values decrease markedly (all below 30) compared to the fixed-transition-probability (FTP) Markov-switching model, especially for Australia, Brazil, and Russia. Clearly, the TVTP Markov-switching model improves the fit and classification of low-volatility and high-volatility sovereign CDS market states. We also examine whether the estimated TVTP models (unconstrained) significantly outperform the corresponding FTP (constrained) models by conducting a log-likelihood ratio (LR) test. The test statistic is calculated as follows:

$$LR = 2 \times [L_{TVTP}(\theta) - L_{FTP}(\theta)]$$

where L_{TVTP} and L_{FTP} are the log-likelihoods of the unconstrained and constrained models, respectively, and θ denotes the parameter vector. The null hypothesis asserts that the unconstrained model does not significantly improve over the constrained model. The associated statistic follows a chi-squared distribution with degrees of freedom equal to the number of additional parameters estimated in the TVTP model that are not included in the FTP model. The results show that we can reject the null hypothesis for Australia, Brazil, and Russia, indicating that the TVTP model is superior to the FTP model. The evidence, however, is insufficient to support the TVTP over the FTP model for Norway.

The enhancement in regime classification is also supported by the smoothed probability plots of the high-volatility regime in Figure 4.3, which show a clearer pattern of switching between crisis and tranquil states than those from the fixed model. The smoothed transition probabilities for Australia and Brazil derived from the TVTP Markov-switching model are noticeably less volatile than those estimated under the FTP model specification. Notably, the probabilities tend to spike during the Eurozone debt crisis, the 2014-16 commodity price slump, and the COVID-19 pandemic. However, Norway remains the

exception, with its smoothed probabilities highly volatile, especially between January 2013 and April 2021 (the period leading up to the Russian invasion of Ukraine).[41]

Wald tests evaluating whether the parameters differ statistically across regimes are displayed in Table 4.8. The null hypothesis of equal ΔCOMM coefficients between the two regimes is rejected for Brazil, Norway, and Russia, indicating that the estimated coefficients vary across regimes. For Australia, consistent with the FTP Markov-switching regression, the Wald test also rejects only the null hypothesis that SIGMA is equal across states, suggesting that the relationship between Australia's SovCDS and the dependent variables remains stable, while volatility changes fundamentally between regimes.

4.5.3.2 ***Quantile regression***

We have established that the impact of commodity price fluctuations varies between crisis and non-crisis periods. The summary statistics reported in Table 4.2 highlight the non-normality of the SovCDS spread change series. The notable differences between the means and medians suggest skewed distributions with extreme outliers or heavy tails. While the preceding analyses appropriately modelled the conditional mean of the SovCDS changes, they do not provide a complete view of the distributional relationship between SovCDS spreads and the covariates.

Quantile regression provides a more detailed analysis of how sovereign risk relates to commodity prices by illustrating variations in SovCDS responses across different quantiles. As a flexible and robust modelling framework, QR extends beyond traditional least-squares regression by modelling the entire conditional distribution rather than just the mean. It is especially useful when the assumptions of linear regression—such as linearity, homoscedasticity, independence, or normality—are not met. Therefore, QR is robust to non-normal errors, heavy-tailed distributions, and outliers. Since it does not require a specific parametric form for the response's conditional distribution, it estimates the conditional quantiles of the response variable in a general linear model, enabling evaluation of regressor effects at various points in the dependent variable's distribution (Davino et al., 2013).

The linear regression model in equation (4.12) can be reformulated to put it in the context of the quantile regression methodology as follows:

[41] We also explore different versions of the model in equation (4.13), such as specifications where coefficients (slopes and intercepts) do not switch regimes, although the variance (SIGMA) can change. Unfortunately, these attempts are unsuccessful for Norway.

$$Q_\tau(\Delta SovCDS_t|W_t) = \alpha^\tau + \sum_{i=1}^{3} \beta_i^\tau \Delta SovCDS_{t-i} + \gamma^\tau \Delta COMM_t + \Delta X_t' \delta^\tau \qquad (4.16)$$

where Q_τ denotes the τth conditional quantile of the SovCDS spread change, $0 < \tau < 1$. W_t is a vector including all the independent variables, with X_t denoting the vector of control variables, including the orthogonalized variables. In turn, α^τ, β_i^τ, γ^τ and δ^τ, are the parameters to be estimated for the different quantiles.[42]

Tables 4.9a and 4.9b display the estimated 5th, 25th, 50th, 75th, and 95th conditional quantiles for the sampled countries. It is important to note that the range of the conditional quantiles reflects different economic periods. The extreme upper quantile corresponds to a crisis period characterised by high sovereign credit risk; the intermediate quantiles indicate moderate sovereign credit market conditions; and the lower quantile relates to quiet periods with low sovereign credit risk. This enables us to assess whether the sensitivity of SovCDS spreads to commodity price fluctuations is more pronounced during periods of high sovereign credit risk than during periods of moderate or low risk. The effect is likely to be asymmetric, with the response of ΔSovCDS to an explanatory variable differing between crisis and tranquil market conditions.

Across all quantiles, ΔCOMM demonstrates negative (favourably) effects on changes in the SovCDS spread for all countries. The coefficients are highly statistically significant (at the 1% level) across all quantiles for the sampled countries, except for the 5th and 95th quantiles of Norway's SovCDS, which are significant at the 5% level. We also note that the estimated ΔCOMM coefficients at each quantile for Norway are approximately half the size of those in the other countries considered. The results show that the impact of commodity price changes is most pronounced in Brazil across all quantiles. This aligns with observations that countries with stronger fundamentals have greater resilience to shocks, with robust domestic fundamentals helping to buffer against shocks in global market sentiment (Csonto and Ivaschenko, 2013).

The magnitudes of the ΔCOMM coefficients are significantly larger at the 95th quantile compared to the intermediate quantiles (0.25, 0.5, and 0.75), particularly for Australia and Norway. Conversely, the difference between the magnitudes of the extreme upper quantile and the intermediate quantiles' coefficients appears to be quite small for EMEs. This suggests that investors in the SovCDS of countries with lower credit ratings may

[42] Please refer to the appendix for a detailed discussion of the quantile regression approach.

need to monitor commodity market developments closely, as such developments could pose considerable risks (Boehm et al., 2021).

Foreign exchange returns have a highly significant positive effect across all quantiles of the SovCDS spread changes for Brazil and Russia. In contrast, the effect is insignificant at the 95th quantile for Australia. An increase in domestic stock market returns (SR) markedly narrows emerging-market SovCDS spreads across all quantiles, but is significant only for intermediate quantiles in Australia. Domestic factors generally have insignificant effects across all quantiles of Norway's SovCDS.

The estimates indicate that the coefficients on ΔSP500 are negative and highly statistically significant across all quantiles of the spread distributions for the sampled countries. This supports our Markov-switching regression findings and those of Ang and Longstaff (2013), who observe that US stock returns significantly influence sovereign CDS spreads. We find a highly statistically significant positive effect of ΔVIX on changes in Brazil's and Russia's SovCDS spreads across all quantiles. The ΔVIX coefficients are significant at all quantiles for Australia, whereas they are insignificant at the extreme right tail (95th quantile) for Norway.

In line with the OLS and Markov-switching regression results, ΔMOVE does not offer significant insights into explaining the conditional quantiles of ΔSovCDS, except for the intermediate quantiles in Australia. Changes in the TED spread generally have negligible effects on SovCDS spreads in Australia and Russia across the quantiles. Variations in the US 5-year Treasury bond yield (a proxy for the global bond market rate) show no explanatory power across the quantiles for the sampled countries.

Comparing the explanatory power across quantiles in the quantile regressions, we observe that pseudo-R^2 values substantially differ across quantiles for Norway and somewhat for Australia.[43] The pseudo-R^2 values are consistently higher at the extreme upper quantile (95^{th}) across all countries, suggesting a greater influence of the explanatory variables when sovereign credit risk is heightened.

4.5.3.3 Alternative measure of global commodity prices

We perform a final robustness check by estimating the Markov regime-switching model using an alternative measure of global commodity prices. For this test, we utilise the Bank

[43] The pseudo-R-squared measures goodness of fit in quantile regression analysis (Koenker and Machado, 1999). It measures the proportion of the variation in the dependent variable explained by the covariates for each specified quantile. It is similarly interpreted as the OLS R-squared.

of America Merrill Lynch Commodity Index (MLCX), which selects commodities based on liquidity and importance to the global economy, with a particular emphasis on downstream commodities.

Estimation results presented in Tables 4.10a and 4.10b show that most of our baseline FTP model findings using the S&P GSCI index remain unchanged when an alternative commodity index is used. Testing for equality of coefficients confirms the baseline results that changes in the commodity index do not have significant asymmetric effects on changes in Australia's SovCDS spreads.[44] A difference worth noting is that high commodity prices are estimated also to have a statistically significant (at the 5% level) negative effect on changes in Norway's SovCDS spreads during the low-volatility regime.

The domestic variables ΔFX and SR are highly significant in both regimes for Brazil, contrary to the baseline FTP model results. The estimation results show a significant positive effect of the US 5-year Treasury bond yield on Brazil's SovCDS spread during the low-volatility state but a significantly negative effect during the high-volatility state. It is also estimated to have a weakly significantly positive effect on Australia's spreads.[45]

4.5.4 Economic Implications

Our research shows that higher commodity prices are linked to lower sovereign CDS spreads in countries that depend heavily on commodity exports. The effect of commodity prices is stronger for EMEs than for AEs, in both stable and volatile periods. We find that sovereign CDS sensitivity to commodity prices is higher during high-volatility regimes than during tranquil times. As a result, a negative shock to commodity prices can significantly increase sovereign CDS spreads during turbulent periods, as market perceptions of default risk worsen. Wider CDS spreads usually lead to lower bond prices and higher borrowing costs for governments and companies (Culp et al., 2016), which can negatively impact consumption, investment, output, employment, and exchange rates. During stressful times, rising CDS spreads can also intensify financial instability through feedback loops, as domestic banks often hold large amounts of their own country's debt.

The estimation results suggest that, among the sampled countries, Norway's sovereign CDS spread is least affected by commodity price shocks across regimes, with a

[44] Wald test results available upon request.
[45] Changes in the MLCX tend to have lower correlations with the foreign variables and the domestic variables, compared to the GSCI measure (statistics available upon request). Hence, multicollinearity issues are not severe. However, in addition to the orthogonalizations specified in equation (4.11), we further orthogonalize changes in the logged VIX with respect to changes in MLCX to mitigate multicollinearity.

significant effect only during crisis regimes. While the results indicate that increasing global financial stress raises the likelihood of shifting from the tranquil to the high-volatility regime for Australia, Brazil, and Russia, this is not observed for Norway. However, there is some evidence that high commodity prices reduce the probability of a switch from a calm state to a high-volatility regime in Norway.

This is consistent with the observation that strong domestic fundamentals enhance resilience to negative global shocks and help shield against shifts in global market sentiment (Csonto and Ivaschenko, 2013). Norway's credit fundamentals are particularly strong, thanks to its wealth in the public sector, prudent management of oil revenues, resilient external position, and robust institutions. These factors act as crucial buffers against economic shocks. Our analysis indicates that markets highly value solid credit fundamentals. During times of increased global financial stress, investors become more cautious, seeking to manage exposure to sovereign default risk and preserve the real value of their assets. As a result, they favour policies that enhance creditworthiness.

As outlined in Section 4.1.1, there are differences among these commodity exporters, highlighting the need for tailored economic policies. Strengthening institutions and policymaking can enhance credit fundamentals, increasing investor confidence even during difficult economic periods. Countries with robust institutions are less likely to default during downturns, avoiding costs that could harm their long-term economic prospects.

A robust fiscal policy framework is essential to decrease the economy's vulnerability to adverse commodity price shocks. Fiscal rules, enforced by independent institutions that oversee and ensure compliance with numerical targets, can improve debt sustainability and reduce sovereign risk. Building fiscal buffers during periods of stability (e.g., savings in the form of liquidity or liquid assets) can act as self-insurance against drops in commodity prices, support countercyclical fiscal policies, and help prevent external debt growth when export prices are unfavourable (UNCTAD, 2019). This should boost confidence among investors and stakeholders.

Commodity-funded sovereign wealth funds with clear policy aims, such as stabilising the budget during commodity price fluctuations (stabilisation funds) and building wealth for future generations (savings funds), help buffer against revenue volatility. Stabilisation funds can support the implementation of countercyclical fiscal policies. Savings funds can aid diversification, for example, by using resource income to acquire other

assets, thereby improving a country's net debt position, which has been proven to be a key factor influencing sovereign funding costs.

The build-up of external debt in countries dependent on commodity exports presents a substantial risk. Falling commodity prices increase the relative cost of debt service, limiting government policy options. Employing hedging instruments could help commodity-exporting nations stabilise their fiscal positions and reduce budgetary uncertainty. For example, instruments linked to commodity prices, such as commodity-linked bonds, allow a country's debt payments to move with the prices of its main export commodities. These bonds help ease the burden on sovereign balance sheets during economic downturns that might otherwise lead to default.

4.6 Conclusion

Following the 2008 global financial crisis, government debt increased significantly in some countries that heavily depend on commodity exports. The decline in commodity prices during 2014-2016 and the COVID-19 pandemic strained sovereign credit fundamentals, revealing vulnerabilities as multiple sovereign borrowers were downgraded. This chapter explores how fluctuations in global commodity prices affect sovereign credit risk. We focus on two advanced economies, Australia and Norway, and two emerging economies, including Brazil and Russia.

Recent research suggests that sovereign debt pricing can follow non-linear patterns, as observed by Delatte et al. (2017). However, many empirical studies rely on linear regression models, largely overlooking the asymmetric nature of sovereign debt dynamics. To fill this gap, we investigate whether commodity price changes influence sovereign CDS spreads differently during crisis versus non-crisis periods, employing a two-regime Markov-switching regression model. Our study analyses weekly five-year CDS spreads as a proxy for sovereign credit risk, covering the period from December 2008 to February 2022.

Estimation results indicate that increases in commodity prices significantly reduce sovereign CDS spreads in Australia, Brazil, and Russia during both crisis and stable periods. We observe that this effect is statistically insignificant during non-crisis periods in Norway. The impact of global commodity price fluctuations on sovereign CDS spreads is notably stronger during crises than in non-crisis periods. Furthermore, the magnitude of this effect is considerably larger in emerging economies compared to developed countries. Findings show that changes in commodity prices have the least impact on Norway's sovereign CDS

spreads, suggesting greater resilience to adverse shocks, whereas the effect is greatest on Russia's. This aligns with various researchers and commentators who attribute Norway's resilience to its strong institutions and prudent fiscal policies supported by its sovereign wealth fund.

As part of robustness checks, we estimate a time-varying transition-probability Markov-switching model, which allows us to explore the factors influencing transition probabilities. We consider commodity prices and the OFR Financial Stress Index (OFR FSI) as informational variables that may trigger regime switching. Our findings indicate that higher financial stress increases the likelihood that sovereign CDS spreads enter a high-volatility regime in Australia, Brazil, and Russia. Results suggest that rising commodity prices increase the likelihood of remaining in a non-crisis state in Norway but, conversely, raise the likelihood of a switch from a low-volatility state to a crisis regime in Russia.

Furthermore, quantile regressions show that commodity price returns significantly influence changes in sovereign CDS spreads across all quantiles for all countries. Across all quantiles, changes in emerging-economy sovereign CDS spreads are more sensitive to commodity price fluctuations than those in advanced-economy spreads, with Norway's spreads exhibiting the least sensitivity.

This chapter provides valuable insights for policymakers and sovereign debt managers in countries that depend on commodity exports. It illustrates how fluctuations in commodity prices can impact sovereign risk under different market conditions. During economic downturns, some economies struggle to offset the effects of commodity price fluctuations on public finances and debt sustainability. Our research emphasises the importance of commodity-exporting nations implementing strategies that enhance resilience to global shocks in commodity markets. The varied effects of commodity price changes on sovereign CDS spreads across the studied countries can be attributed to differences in their structural characteristics and policy frameworks.

To improve resilience to commodity price declines, countries that produce commodities should seek to diversify their economies. Implementing structural reforms to lower dependence on commodity export revenues, while boosting tax income through a sustained, long-term real hedging strategy that diversifies into non-commodity sectors, will enhance their ability to service sovereign debt during periods of low commodity prices. Norway's successful transition away from oil dependency in recent years highlights the benefits of diversification strategies.

Investors and financial analysts can integrate the regime-dependent features of sovereign CDS spreads into their investment and credit analysis frameworks. Central banks, which often hold substantial amounts of government debt, should consider the implications of developments in commodity markets on their holdings when formulating policy decisions. Future research could further investigate the effects of commodity-sector indices on sovereign CDS spreads, thereby extending the discussions presented in this chapter.

4.7 Tables and figures

4.7.1 Tables

Table 4.1 Data description and sources

Variable name		Frequency	Source
Sovereign Credit Default Swaps			
Australia	COMMONWEALTH OF AU SNR MR 5Y $ - CDS PREM. MID	Daily	DataStream
Brazil	BRAZIL, REPUBLIC OF SNR CR14 5Y $ - CDS PREM. MID	Daily	DataStream
Norway	KINGDOM OF NORWAY SNR CR 5Y $ - CDS PREM. MID	Daily	DataStream
Russia	GOVT OF RUSSIA SNR CR14 5Y $ - CDS PREM. MID	Daily	DataStream
Stock Indices			
Australia, Brazil, Norway	MSCI AUSTRALIA U$ - TOT RETURN IND	Daily	DataStream
Russia	FTSE RUSSIA $ - TOT RETURN IND	Daily	DataStream
Exchange rates			
Australia	AUSTRALIAN $ TO US $ (RFV) - EXCHANGE RATE	Daily	DataStream
Brazil	BRAZILIAN REAL TO US $ (RFV) - EXCHANGE RATE	Daily	DataStream
Norway	NORWEGIAN KRONE TO US $ (RFV) - EXCHANGE RATE	Daily	DataStream
Russia	RUSSIAN ROUBLE TO US $ (RFV) - EXCHANGE RATE	Daily	DataStream
Market Yield on U.S. Treasury Securities at 5-Year Constant Maturity, Continuously Compounded Rate of Change, Not Seasonally Adjusted.		Weekly average (ending Friday)	Federal Reserve Economic Data (https://fred.stlouisfed.org/)
ML Move 1m Bond Volatility Index - Price Index		Daily	DataStream
S&P 500 Composite - Price Index		Daily	DataStream
Ted Spread Rate - Middle Rate		Daily	DataStream
CBOE Volatility Index: VIX, Index, Not Seasonally Adjusted		Weekly average (ending Friday)	Federal Reserve Economic Data
Commodity Indices	- S&P GSCI Commodity Total Return - Return Ind. (OFCL)	Daily	DataStream
	- MLCX Total Return - Return Ind. (OFCL)	Daily	DataStream
The OFR Financial Stress Index (OFR FSI)		Daily	https://www.financialresearch.gov/financial-stress-index/

Notes: Weekly data obtained by averaging daily data (week ending Friday). Weekly data is log-transformed and then differenced except for the Market Yield on U.S. Treasury Securities at 5-Year Constant Maturity, TED spread, and OFR FSI, which are only differenced. Daily data from 12/22/2008 to 2/18/2022. All data retrieved August 20, 2024.

Table 4.2 Descriptive Statistics

		Mean	Med	Max	Min	St.Dev.	Skew	Kurt	Jarque-Bera
Australia	ΔSCDS	-0.31	-0.38	52.31	-31.02	0.06	0.98	13.36	3174.8***
	ΔFX	-0.01	-0.05	8.36	-4.77	0.01	0.60	7.27	562.0***
	SR	0.19	0.35	10.45	-20.70	0.03	-0.98	10.93	1906.6***
Brazil	ΔSCDS	-0.05	-0.33	53.49	-20.20	0.06	1.43	13.81	3570.7***
	ΔFX	0.11	0.04	7.21	-5.25	0.02	0.27	4.08	41.6***
	SR	0.09	0.13	12.14	-25.55	0.04	-0.71	8.21	833.9***
Norway	ΔSCDS	-0.20	-0.02	27.68	-17.83	0.05	0.86	8.38	912.4***
	ΔFX	0.03	0.03	11.62	-5.68	0.01	1.00	11.53	2192.6***
	SR	0.18	0.36	11.26	-22.19	0.03	-0.76	8.35	883.8***
Russia	ΔSCDS	-0.17	-0.50	75.92	-22.63	0.08	1.88	19.34	8034.4***
	ΔFX	0.14	0.00	12.69	-15.02	0.02	0.59	15.25	4325.9***
	SR	0.16	0.33	13.77	-23.19	0.04	-0.63	7.12	530.7***
Global variables	ΔCOMM	-0.02	0.21	8.31	-17.65	0.03	-1.01	8.56	1002.2***
	ΔSP500	0.28	0.48	7.30	-11.95	0.02	-1.38	10.21	1702.7***
	ΔVIX	-0.07	-1.23	77.00	-37.36	0.12	1.11	7.97	844.9***
	ΔMOVE	-0.10	-0.73	33.97	-25.71	0.07	0.56	5.17	170.6***
	Δ5YR	0.03	0.00	28.77	-41.00	6.49	-0.25	6.73	405.8***
	ΔTED	-0.13	-0.20	28.05	-27.08	4.28	0.46	10.30	1546.0***

Note: This table reports descriptive statistics for the variables, based on weekly data from January 2009 to February 2022. All data (except the ΔTED spread and the Δ5YR Treasury Yield changes) are in logarithmic changes and multiplied by 100 for readability. *** denotes statistical significance at the 1% level.

Table 4.3 Correlation between the local and global variables

	ΔCOMM	ΔSP500	ΔVIX	ΔTED	ΔUS5YR	ΔMOVE	SR-AUS	SR-BRZ	SR-NOR	SR-RUS
ΔCOMM	1.0									
ΔSP500	0.6	1.0								
ΔVIX	-0.4	-0.7	1.0							
ΔTED	-0.1	-0.1	0.0	1.0						
ΔUS5YR	0.3	0.3	-0.3	0.1	1.0					
ΔMOVE	-0.1	-0.3	0.4	0.1	0.1	1.0				
SR-AUS	0.6	0.8	-0.6	-0.2	0.2	-0.3	1.0			
SR-BRZ	0.6	0.6	-0.4	-0.1	0.2	-0.2	0.7	1.0		
SR-NOR	0.7	0.8	-0.6	-0.2	0.3	-0.3	0.8	0.7	1.0	
SR-RUS	0.6	0.6	-0.5	-0.1	0.3	-0.2	0.7	0.7	0.7	1.0
ΔFX-AUS	-0.5	-0.6	0.4	0.1	-0.1	0.2	-0.8	-0.7	-0.7	-0.6
ΔFX-BRZ	-0.4	-0.4	0.3	0.1	-0.1	0.2	-0.5	-0.8	-0.5	-0.5
ΔFX-NOR	-0.6	-0.6	0.4	0.1	-0.1	0.2	-0.7	-0.6	-0.8	-0.6
ΔFX-RUS	-0.5	-0.5	0.4	0.1	-0.2	0.2	-0.5	-0.5	-0.6	-0.7

Notes: COMM, SP500, TED, US5YR, MOVE, SR, and FX denote the S&P GSCI composite index, S&P500 index, TED spread, MOVE index, local stock market return, and foreign exchange return, respectively. AUS is Australia, BRZ is Brazil, NOR is Norway, and RUS is Russia. Δ denotes the first difference.

Table 4.4 Linear models estimation of sovereign CDS spreads

	Australia	Brazil	Norway	Russia
Constant	0.002	0.001	0.001	0.002
	[1.48]	[0.76]	[0.62]	[0.88]
Δ*COMM*	-0.821***	-1.170***	-0.435***	-1.363***
	[-8.16]	[-8.37]	[-5.20]	[-7.89]
SovCDS(-1)	0.268***	0.069**	0.160***	0.136***
	[-7.05]	[2.19]	[2.85]	[3.92]
SovCDS(-2)	-0.101**	-0.082***	0.046	-0.087***
	[-1.98]	[-3.23]	[0.78]	[-2.93]
SovCDS(-3)	0.051	0.049	-0.002	0.009
	[1.41]	[1.28]	[-0.04]	[0.27]
Δ*FX*	0.692***	1.718***	0.161	1.600***
	[2.41]	[13.29]	[0.71]	[11.69]
SR	-0.507**	-0.847***	-0.205	-0.834***
	[-2.89]	[-6.09]	[-1.14]	[-6.54]
Δ*SP500*	-1.870***	-1.432***	-1.048***	-1.905***
	[-8.48]	[-6.50]	[-5.54]	[-6.87]
Δ*VIX*	0.106***	0.147***	0.056***	0.189***
	[5.77]	[8.87]	[3.27]	[7.51]
Δ*TED*	0.001	0.001**	0.001**	0.001
	[1.40]	[2.21]	[2.07]	[1.23]
Δ*MOVE*	0.085*	0.069**	0.011	0.011
	[1.79]	[2.47]	[0.38]	[0.25]
Δ*US5YR*	-0.003	-0.005	0.021	0.005
	[-0.13]	[0.26]	[0.62]	[0.19]
Adjusted R-squared	43.5%	63.0%	19.3%	60.2%
Log likelihood	1120.6	1258.5	1175.0	1120.0
Akaike info criterion	-3.2463	-3.6501	-3.4056	-3.2445
Schwarz criterion	-3.1668	-3.5706	-3.3261	-3.1650
Durbin-Watson stat	2.1	1.9	2.0	1.9

Note: We report *t*-statistics, using heteroskedasticity- and autocorrelation-consistent (HAC) standard errors (Bartlett kernel and Newey-West fixed) in brackets below the coefficient estimates. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. For variable names, please refer to Table 4.3. We orthogonalize the domestic stock market returns (*ΔSR)* by regressing them on ΔCOMM, ΔSP500, and ΔFX (Please note that for Brazil, we also include changes in the TED spread as a regressor). Foreign exchange returns are orthogonalized by regressing on ΔCOMM and ΔSP500. Global stock market returns (ΔSP500) are orthogonalized by regressing them on ΔCOMM and ΔVIX. Changes in the VIX are orthogonalized by regressing them on ΔCOMM.

Table 4.5a Markov-Switching model results

	Australia		Brazil	
	Tranquil	Turbulent	Tranquil	Turbulent
Constant	0.002	0.002	-0.002	0.004
	[0.69]	[0.34]	[-1.08]	[0.77]
Δ*COMM*	-0.543***	-1.094***	-0.695***	-1.474***
	[-4.17]	[-3.01]	[-6.26]	[-8.03]
SovCDS(-1)	0.305***	0.224**	0.089	0.038
	[3.93]	[2.47]	[1.37]	[-0.75]
SovCDS(-2)	-0.003	-0.196	0.043	-0.131**
	[-0.03]	[-1.45]	[0.70]	[-2.46]
SovCDS(-3)	-0.001	0.139	0.106***	-0.026
	[-0.02]	[1.55]	[2.66]	[0.56]
Δ*FX*	0.451*	1.255	1.280***	2.042***
	[1.67]	[1.45]	[4.49]	[5.96]
SR	-0.207	-1.068*	-0.287**	-1.176***
	[-0.92]	[-1.74]	[-2.49]	[-6.07]
Δ*SP500*	-1.401***	-2.068***	-0.968***	-1.739***
	[-3.87]	[-3.67]	[-5.46]	[-3.09]
Δ*VIX*	0.075***	0.203**	0.090***	0.176***
	[3.00]	[2.06]	[4.74]	[4.91]
Δ*TED*	0.001	0.000	0.000	0.001
	[1.49]	[-0.10]	[0.55]	[1.21]
Δ*MOVE*	0.119***	0.276*	0.052	0.095**
	[4.64]	[1.78]	[1.10]	[1.96]
Δ*US5YR*	0.033	-0.072	0.011	-0.014
	[1.39]	[-0.59]	[0.30]	[-0.29]
SIGMA	0.028***	0.076***	0.025***	0.042***
Prob(ii)	0.931	0.783	0.906	0.897
DU(i)	14.5	4.6	10.6	9.7
Durbin-Watson stat	2.04		1.95	
Log likelihood	1227.2		1309.3	
Akaike info criterion	-3.5116		-3.7521	
Schwarz criterion	-3.3260		-3.5665	
RCM	33		48	

Notes: We report z-statistics in brackets below the coefficient estimates. For Australia, the z-statistics are based on Huber–White robust standard errors. ***, **, * denote significance at 1%, 5% and 10% levels, respectively. Prob(ii) denotes the probability of staying under regime ***i*** next period if ***i*** is the current regime. RCM is the regime classification measure. SIGMA refers to the standard deviation of each state. For variable names, please refer to Table 4.3. For orthogonalization operations, refer to Table 4.4. Results from EViews version 12.

Table 4.5b Markov-Switching model results

	Norway		Russia	
	Tranquil	Turbulent	Tranquil	Turbulent
Constant	-0.002**	0.003	-0.003	0.006
	[-2.36]	[-1.01]	[-1.31]	[1.25]
Δ*COMM*	-0.040	-0.668***	-1.064***	-1.881***
	[-1.12]	[-5.67]	[-13.62]	[-9.96]
SovCDS(-1)	0.119***	0.173***	0.130***	0.038
	[3.25]	[2.61]	[3.75]	[0.83]
SovCDS(-2)	-0.031	-0.120	-0.104***	-0.490
	[-0.89]	[-1.47]	[-2.81]	[-1.03]
SovCDS(-3)	0.076**	-0.034	-0.010	-0.026
	[2.11]	[0.55]	[-0.42]	[-0.45]
Δ*FX*	-0.023	0.577*	1.405***	3.176***
	[-0.35]	[1.83]	[13.16]	[6.09]
SR	0.000	0.085	-0.521***	-1.442***
	[0.00]	[0.35]	[-6.02]	[-6.00]
Δ*SP500*	-0.098	-1.591***	-1.231***	-3.965***
	[-1.17]	[-5.18]	[-7.80]	[-8.73]
Δ*VIX*	0.005	0.116***	0.128***	0.328***
	[0.89]	[3.50]	[7.14]	[6.24]
Δ*TED*	0.001**	0.001	0.000	0.002
	[2.43]	[-1.62]	[0.47]	[1.36]
Δ*MOVE*	0.003	-0.021	0.004	0.060
	[0.25]	[-0.45]	[0.12]	[0.92]
Δ*US5YR*	0.009	0.021	-0.032	0.149**
	[1.07]	[0.51]	[-1.34]	[2.13]
SIGMA	0.009***	0.055***	0.036***	0.051***
Prob(ii)	0.767	0.806	0.970	0.916
DU(i)	4.3	5.1	33.8	11.9
Durbin-Watson stat	1.99		1.84	
Log likelihood	1378.1		1194.3	
Akaike info criterion	-3.9533		-3.4152	
Schwarz criterion	-3.7678		-3.2297	
RCM	31		24	

Notes: Please refer to Table 4.5a. Results from EViews version 12.

Table 4.6 Tests for coefficient equality between states for FTP model estimates

	Δ*COMM*	Δ*FX*	*SR*	Δ*SP500*	Δ*VIX*	Δ*TED*	Δ*MOVE*	Δ*5YR*	*SIGMA*
Australia	2.1	0.6	1.7	0.8	1.8	0.1	0.8	0.6	102.2***
	[0.13]	[0.42]	[0.19]	[0.36]	[0.18]	[0.72]	[0.64]	[0.43]	[0.00]
Brazil	11.8***	1.7	13.1***	1.2	3.4*	0.2	0.3	0.1	30.9***
	[0.00]	[0.19]	[0.00]	[0.26]	[0.06]	[0.64]	[0.58]	[0.75]	[0.00]
Norway	26.5***	2.5*	0.1	21.6***	10.6***	0.2	0.2	0.1	345.3***
	[0.00]	[0.12]	[0.72]	[0.00]	[0.00]	[0.62]	[0.63]	[0.80]	[0.00]
Russia	15.1***	10.7***	12.2***	32.1***	12.2***	1.3	0.6	5.2**	17.0***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[025]	[0.44]	[0.02]	[0.00]

Notes: The table reports chi-squared values and associated p-values (in brackets) for testing symmetry between the low- and high-volatility states. Sigma represents the standard error of the estimate. The superscripts ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. For variable names, please refer to Table 4.3. Results from EViews version 12.

Table 4.7a TVTP Markov-Switching model results

		Australia		***Brazil***	
		Regime 1	Regime 2	Regime 1	Regime 2
	Constant	0.002 [0.77]	0.003 [0.41]	-0.003 [-1.55]	0.010 [1.10]
	Δ*COMM*	-0.567*** [-4.98]	-1.135*** [-3.30]	-0.848*** [-12.03]	-1.649*** [-7.80]
	SovCDS(-1)	0.304*** [5.68]	0.231** [2.48]	0.124*** [2.94]	-0.017 [-0.29]
	SovCDS(-2)	0.014 [0.25]	-0.207** [-2.19]	-0.061 [-1.52]	-0.132** [-2.25]
	SovCDS(-3)	-0.005 [-0.14]	0.145* [1.65]	0.039 [1.01]	0.104** [2.12]
	Δ*FX*	0.484* [1.92]	1.222 [1.06]	1.483*** [8.91]	2.566*** [7.51]
	SR	-0.220 [-1.25]	-1.094* [-1.719]	-0.615*** [-5.52]	-1.328*** [-4.37]
	Δ*SP500*	-1.413*** [-4.39]	-1.994*** [-3.32]	-1.189*** [-5.72]	-1.737** [-2.12]
	Δ*VIX*	0.075*** [3.22]	0.225* [1.90]	0.152*** [8.82]	0.078* [1.85]
	Δ*MOVE*	0.071** [2.06]	0.137 [0.81]	0.007 [0.24]	0.184*** [2.84]
	Δ*TED*	0.001* [1.74]	0.000 [-0.19]	0.001*** [2.69]	0.000 [-0.82]
	Δ*US5YR*	0.035 [1.62]	-0.093 [-0.70]	-0.014 [-0.71]	0.054 [-0.97]
	SIGMA	0.029***	0.078***	0.030***	0.045***
Transition Matrix Parameters					
P11	*α1,11*		3.235** [2.48]		4.592*** [4.53]
	β1,11 (ΔCOMM(-1))		-6.227 [-0.16]		38.140 [1.32]
	γ1,11 (ΔlnFSI(-1))		-1.643*** [-2.67]		-1.988** [-2.13]
P21	*α2,21*		-1.556** [-2.37]		-2.412*** [-2.91]
	β2,21 (ΔCOMM(-1))		17.061 [1.17]		7.956 [0.12]
	γ2,21 (ΔlnFSI(-1))		0.428 [1.00]		0.161 [-0.22]
Durbin-Watson stat			2.1		1.9
Akaike info criterion			-3.5155		-3.7702
Schwarz criterion			-3.3034		-3.5581
Log likelihood (LL)			1232.5		1319.5
RCM			25		22
Log-likelihood ratio (LR)			10.6300		20.3840
	(p-value)		(0.031)		(0.000)

Notes: FSI denotes the OFR Financial Stress Indicator. Please refer to Table 4.5 for additional notes. Results from EViews version 12.

Table 4.7b TVTP Markov-Switching model results

	Norway		***Russia***	
	Regime 1	Regime 2	Regime 1	Regime 2
Constant	-0.002**	0.004	-0.002	0.009
	[-2.27]	[1.11]	[-0.98]	[1.44]
Δ*COMM*	-0.028	-0.665***	-1.127***	-2.010***
	[-0.48]	[-5.85]	[-15.47]	[-9.08]
SovCDS(-1)	0.122***	0.175***	0.138***	0.116*
	[3.29]	[2.67]	[3.99]	[1.82]
SovCDS(-2)	-0.024	0.113	-0.146***	-0.034
	[-0.66]	[1.39]	[-3.97]	[-0.56]
SovCDS(-3)	0.085**	-0.028	0.008	0.002
	[2.46]	[-0.45]	[0.33]	[0.04]
Δ*FX*	-0.032	0.576*	1.391***	3.371***
	[-0.44]	[1.82]	[12.99]	[4.60]
SR	0.013	0.080	-0.561***	-1.345***
	[0.16]	[0.34]	[-5.39]	[-5.33]
Δ*SP500*	-0.087	-1.564***	-1.349***	-4.500***
	[-1.04]	[-5.07]	[-8.97]	[-7.93]
Δ*VIX*	0.006	0.116***	0.138***	0.309***
	[0.98]	[3.53]	[7.28]	[5.58]
Δ*MOVE*	0.004	-0.020	0.004	-0.032
	[0.28]	[-0.43]	[0.13]	[-0.45]
Δ*TED*	0.001**	0.001	0.000	0.005***
	[2.28]	[1.62]	[0.32]	[2.82]
Δ*US5YR*	0.008	0.020	-0.022	0.102
	[1.00]	[0.50]	[-0.96]	[1.05]
SIGMA	0.009***	0.055***	0.037***	0.049***
Transition Matrix Parameters				
P11 *α1,11*		1.324***		4.545***
		[5.10]		[4.94]
β1,11 (ΔCOMM(-1))		18.588*		-60.801***
		[1.82]		[-2.69]
γ1,11 (ΔlnFSI(-1))		0.226		-1.423**
		[0.23]		[-1.99]
P21 *α2,21*		-1.507***		-2.888***
		[-5.80]		[-4.04]
β2,21 (ΔCOMM(-1))		-0.584		-49.678
		[-0.07]		[-1.50]
γ2,21 (ΔlnFSI(-1))		0.374		-0.470
		[1.04]		[-0.54]
Durbin-Watson stat		2.0		1.9
Akaike info criterion		-3.9523		-3.4304
Schwarz criterion		-3.7402		-3.2184
Log likelihood (LL)		1381.7		1203.5
RCM		29		19
Log-likelihood ratio (LR)		7.2660		18.3800
(p-value)		(0.122)		(0.001)

Notes: FSI denotes the OFR Financial Stress Indicator. Please refer to Table 4.5 for additional notes.

Table 4.8 Tests for coefficient equality between states for TVTP model estimates

	ΔCOMM	*ΔFX*	*SR*	*ΔSP500*	*ΔVIX*	*ΔTED*	*ΔMOVE*	*ΔUS5YR*	*SIGMA*
Australia	2.4 [0.12]	0.3 [0.60]	1.9 [0.16]	0.7 [0.40]	2.8* [0.09]	0.3 [0.61]	0.4 [0.54]	2.5 [0.12]	110.1*** [0.00]
Brazil	12.8*** [0.00]	0.9 [0.34]	4.7** [0.03]	0.9 [0.35]	0.7 [0.40]	0.9 [0.34]	2.7 [0.10]	2.0 [0.16]	11.7*** [0.00]
Norway	29.2*** [0.00]	3.4* [0.06]	0.1 [0.76]	21.8*** [0.00]	9.3*** [0.00]	0.3 [0.57]	0.2 [0.66]	0.1 [0.76]	362.6*** [0.00]
Russia	14.2*** [0.00]	29.2*** [0.00]	11.3*** [0.00]	56.8*** [0.00]	8.6*** [0.00]	6.9*** [0.01]	0.0 [0.87]	5.3** [0.02]	4.0** [0.05]

Notes: The table reports chi-squared values and associated p-values (in brackets) for testing symmetry between the low- and high-volatility states. Sigma represents the standard error of the estimate. The superscripts ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4.9a Quantile regression estimates

Quantiles	*q(5)*	*q(25)*	*q(50)*	*q(75)*	*q(95)*
Australia					
Constant	-0.068***	-0.021***	0.003	0.022***	0.078***
	[-11.38]	[-8.95]	[1.62]	[8.04]	[10.79]
Δ*COMM*	-0.890***	-0.565***	-0.620***	-0.798***	-1.315***
	[-4.05]	[-4.79]	[-5.84]	[-6.43]	[-4.94]
SovCDS(-1))	0.316**	0.240***	0.254***	0.264***	0.366***
	[2.33]	[4.26]	[6.57]	[6.64]	[3.81]
SovCDS(-2)	-0.172*	-0.027	-0.072	-0.022	-0.095
	[-1.85]	[-0.48]	[-1.53]	[-0.55]	[-0.93]
SovCDS(-3)	0.144	-0.011	0.020	0.057	-0.006
	[1.61]	[-0.27]	[0.47]	[1.27]	[-0.05]
Δ*FX*	1.700***	0.688**	0.567***	0.567***	0.043
	[3.03]	[2.37]	[3.40]	[3.45]	[0.08]
SR	-0.673	-0.618***	-0.281**	-0.544**	-0.781
	[-1.55]	[-2.77]	[-2.28]	[-2.55]	[-1.52]
Δ*SP500*	-1.836***	-1.465***	-1.506***	-1.756***	-1.695***
	[-4.09]	[-6.12]	[-5.79]	[-6.43]	[-3.07]
Δ*VIX*	0.101*	0.092***	0.067***	0.096***	0.133**
	[1.72]	[3.87]	[3.33]	[4.24]	[2.13]
Δ*TED*	0.000	0.001	0.001	0.001*	0.002*
	[0.19]	[1.44]	[1.64]	[1.90]	[1.68]
Δ*MOVE*	0.096	0.088*	0.080***	0.069*	0.041
	[1.15]	[1.87]	[2.80]	[1.88]	[0.36]
Δ*US5YR*	0.028	0.013	0.014	0.030	-0.018
	[0.35]	[0.43]	[0.62]	[-0.99]	[-0.23]
Pseudo R-sq	24.7%	21.2%	20.6%	26.2%	33.3%
Norway					
Constant	-0.071***	-0.017***	0.000	0.017***	0.073***
	[-15.58]	[-6.98]	[0.02]	[5.53]	[7.42]
Δ*COMM*	-0.453**	-0.324***	-0.203***	-0.354***	-0.631**
	[-2.24]	[-3.49]	[-2.72]	[-3.28]	[-2.52]
SovCDS(-1))	0.070	0.116*	0.177***	0.226***	0.176
	[0.80]	[1.67]	[3.83]	[4.11]	[1.52]
SovCDS(-2)	-0.058	0.039	-0.010	-0.058	0.053
	[-0.75]	[0.74]	[-0.27]	[-1.11]	[0.37]
SovCDS(-3)	0.108	-0.038	0.024	0.020	-0.087
	[1.16]	[-0.76]	[0.79]	[0.35]	[-0.88]
Δ*FX*	1.103*	0.257	0.068	0.065	-0.195
	[1.77]	[1.01]	[0.59]	[0.34]	[-0.32]
SR	-0.111	-0.109	-0.090	-0.200	-0.501
	[-0.36]	[-0.52]	[-0.89]	[-1.19]	[-1.33]
Δ*SP500*	-0.690**	-0.913***	-0.518***	-1.057***	-2.249***
	[-1.98]	[-3.65]	[-2.97]	[-3.51]	[-4.26]
Δ*VIX*	0.082**	0.043**	0.025**	0.036**	-0.024
	[1.98]	[2.24]	[2.06]	[2.24]	[-0.38]
Δ*TED*	0.002**	0.001	0.001**	0.001**	0.001
	[2.19]	[1.53]	[2.16]	[2.05]	[0.59]
Δ*MOVE*	0.017	0.013	0.003	0.039	-0.015
	[0.24]	[0.34]	[0.12]	[1.39]	[-0.16]
Δ*US5YR*	0.040	0.055*	0.008	-0.025	-0.036
	[0.65]	[1.82]	[0.46]	[-0.95]	[-0.52]
Pseudo R-sq	14.5%	7.6%	5.1%	9.9%	20.2%

Notes: This table reports the QR coefficient estimates of the model in Equation. (??) for each country. The t-statistics in brackets are based on bootstrap standard errors. The asterisk (***, **, *) denotes statistical significance at the 1%, 5%, and 10% levels, respectively. For variable names, please refer to Table 4.3.

Table 4.9b Quantile regression estimates

Quantiles	*q(5)*	*q(25)*	*q(50)*	*q(75)*	*q(95)*
Brazil					
Constant	-0.061***	-0.023***	0.000	0.025***	0.064***
	[-13.72]	[-10.65]	[-0.24]	[9.60]	[13.17]
Δ*COMM*	-1.080***	-0.926***	0.994***	-1.138***	-1.366***
	[-6.46]	[-9.75]	[-11.15]	[-10.14]	[-6.22]
SovCDS(-1))	0.081	0.075**	0.109***	0.123**	0.029
	[0.92]	[2.09]	[2.98]	[2.78]	[0.49]
SovCDS(-2)	-0.198***	-0.066	-0.072**	-0.106**	-0.005
	[-2.81]	[-1.26]	[-2.06]	[-2.27]	[-0.07]
SovCDS(-3)	0.024	-0.005	0.057**	0.050	0.108*
	[0.27]	[-0.14]	[2.07]	[1.41]	[1.75]
Δ*FX*	1.653***	1.722***	1.608***	1.653***	1.877***
	[6.22]	[11.23]	[11.60]	[10.30]	[7.57]
SR	-0.953***	-0.636***	-0.677***	-0.847***	-0.991***
	[-4.29]	[-4.81]	[-4.69]	[-5.83]	[-4.12]
Δ*SP500*	-1.190***	-1.232***	-1.317***	-1.378***	-1.709***
	[-4.19]	[-7.67]	[-7.37]	[-4.98]	[-4.31]
Δ*VIX*	0.158***	0.127***	0.125***	0.183***	0.213***
	[3.72]	[7.06]	[8.51]	[8.25]	[5.01]
Δ*TED*	0.002**	0.001*	0.001***	0.001	0.001
	[2.37]	[1.74]	[1.94]	[0.89]	[1.00]
Δ*MOVE*	0.094	0.059	0.060**	0.043	0.014
	[1.30]	[1.35]	[2.01]	1.22]	[0.18]
Δ*US5YR*	-0.002	-0.010	0.016	-0.014	0.012
	[-0.47]	[-0.41]	[-0.75]	[-0.48]	[0.19]
Pseudo R-sq	38.8%	35.2%	35.2%	37.2%	47.2%
Russia					
Constant	-0.072***	-0.028***	0.000	0.029***	0.081***
	[-14.68]	[-11.71]	[-0.19]	[10.75]	[9.95]
Δ*COMM*	-0.732***	-0.933***	-0.924***	-0.855***	-1.238***
	[-3.90]	[-8.14]	[-11.00]	[-6.12]	[-3.52]
SovCDS(-1))	0.159**	0.141***	0.116***	0.134***	0.162*
	[2.16]	[3.71]	[3.07]	[3.26]	[1.82]
SovCDS(-2)	-0.167**	-0.090**	-0.089**	-0.050	-0.107
	[-2.38]	[-2.16]	[-2.27]	[-1.05]	[-1.50]
SovCDS(-3)	0.003	0.009	-0.007	-0.024	0.047
	[0.05]	[0.24]	[-0.20]	[-0.80]	[0.56]
Δ*FX*	1.972***	1.506***	1.598***	1.564***	1.503***
	[8.39]	[9.05]	[7.96]	[8.21]	[4.67]
SR	-0.900***	-0.757***	-0.769***	-0.745***	-0.757***
	[-3.90]	[-6.17]	[-5.87]	[-3.98]	[-3.29]
Δ*SP500*	-1.678***	-1.403***	-1.615***	-1.780***	-2.494***
	[-4.85]	[-6.80]	[-7.84]	[-8.57]	[-4.85]
Δ*VIX*	0.187***	0.187***	0.180***	0.166***	0.238***
	[4.24]	[8.16]	[10.37]	[6.26]	[4.40]
Δ*MOVE*	-0.092	-0.028	-0.005	0.028	0.056
	[-1.22]	[-0.68]	[-0.14]	[0.74]	[0.60]
Δ*TED*	0.001	0.000	0.001*	0.001	0.000
	[0.66]	[0.10]	[1.82]	[1.35]	[-0.33]
Δ*US5YR*	-0.062	-0.029	0.009	0.007	0.055
	[-0.12]	[-0.70]	[0.32]	[0.23]	[0.73]
Pseudo R-sq	36.6%	33.7%	33.4%	35.5%	44.7%

Notes: This table reports the QR coefficient estimates of the model in Equation. (??) for each country. The t-statistics in brackets are based on bootstrap standard errors. The asterisk (***, **, *) denotes statistical significance at the 1%, 5%, and 10% levels, respectively. For variable names, please refer to Table 4.3.

Table 4.10a Markov-Switching model results [Alternative commodity price index]

	Australia		Brazil	
	Tranquil	Turbulent	Tranquil	Turbulent
Constant	0.002	0.003	-0.003	0.004
	[0.70]	[0.38]	[-1.57]	[1.22]
Δ*COMM*	-2.510***	-5.328**	-2.798***	-8.325***
	[-3.97]	[-2.27]	[-6.51]	[-7.87]
SovCDS(-1))	0.304***	0.223**	0.195***	-0.001
	[4.11]	[2.47]	[4.23]	[-0.02]
SovCDS(-2)	0.001	-0.201	-0.110**	-0.078
	[0.01]	[-1.57]	[-2.48]	[-1.63]
SovCDS(-3)	-0.001	0.141	-0.058	0.095**
	[-0.02]	[1.63]	[-1.11]	[2.36]
Δ*FX*	0.504*	1.353	1.367***	2.136***
	[1.91]	[1.45]	[8.01]	[10.96]
SR	-0.215	-1.070*	-0.425***	-1.194***
	[-1.00]	[-1.73]	[-4.81]	[-5.94]
Δ*SP500*	-1.447***	-2.220***	-1.553***	-1.583***
	[-4.36]	[-3.99]	[-7.03]	[-6.59]
Δ*VIX*	0.094***	0.239**	0.176***	0.179***
	[3.63]	[2.30]	[8.49]	[6.61]
Δ*TED*	0.001	0.000	0.001*	0.001
	[1.57]	[-0.12]	[1.95]	[0.97]
Δ*MOVE*	0.070**	0.139	0.000	0.106**
	[2.32]	[1.00]	[-0.01]	[2.25]
Δ*US5YR*	0.039*	-0.064	0.063**	-0.074**
	[1.70]	[-0.56]	[2.32]	[-2.16]
SIGMA	0.028***	0.077***	0.022***	0.043***
Prob(ii)	0.932	0.781	0.857	0.856
DU(i)	14.7	4.6	7.0	7.0
Durbin-Watson stat	2.03		1.91	
Log likelihood	1227.4		1318.7	
Akaike info criterion	-3.5121		-3.7795	
Schwarz criterion	-3.3266		-3.5940	
RCM	32		49	

Notes: commodity measure is the Bank of America Merrill Lynch Commodity Index (MLCX). Please refer to Table 4.5 for additional notes.

Table 4.10b Markov-Switching model results [Alternative commodity price index]

	Norway		Russia	
	Tranquil	Turbulent	Tranquil	Turbulent
Constant	-0.002**	0.004	-0.002	0.011
	[-2.35]	[1.10]	[-1.11]	[1.61]
Δ*COMM*	-0.443**	-2.312***	-4.342***	-7.642***
	[-2.29]	[-2.95]	[-7.51]	[-5.40]
SovCDS(-1))	0.119***	0.163**	0.150***	0.115*
	[3.61]	[2.46]	[3.90]	[1.94]
SovCDS(-2)	-0.027	0.127	-0.143***	-0.053
	[-0.76]	[1.57]	[-3.00]	[-0.87]
SovCDS(-3)	0.076**	-0.031	0.002	-0.037
	[2.17]	[-0.49]	[0.08]	[-0.57]
Δ*FX*	-0.053	0.704**	1.449***	2.958***
	[-0.82]	[2.35]	[11.77]	[4.77]
SR	0.001	0.122	-0.514***	-1.369***
	[0.01]	[0.51]	[-4.57]	[-5.34]
Δ*SP500*	-0.082	-1.751***	-1.627***	-4.739***
	[-1.13]	[-5.94]	[-9.88]	[-8.84]
Δ*VIX*	0.004	0.149***	0.179***	0.390***
	[0.75]	[4.65]	[7.945]	[7.56]
Δ*TED*	0.001**	0.001*	0.000	0.002
	[2.35]	[1.68]	[0.11]	[1.30]
Δ*MOVE*	0.003	-0.027	0.004	-0.013
	[0.26]	[-0.59]	[0.12]	[-0.20]
Δ*US5YR*	0.011	0.016	-0.028	0.101
	[1.39]	[0.38]	[-1.07]	[1.18]
SIGMA	0.009***	0.055***	0.036***	0.050***
Prob(ii)	0.763	0.801	0.970	0.910
DU(i)	4.2	5.0	33.6	11.2
Durbin-Watson stat	1.98		1.94	
Log likelihood	1381.3		1193.5	
Akaike info criterion	-3.9630		-3.4129	
Schwarz criterion	-3.7774		-3.2274	
RCM	31		25	

Notes: commodity measure is the Bank of America Merrill Lynch Commodity Index (MLCX). Please refer to Table 4.5 for additional notes.

4.7.2 Figures

Figure 4.1 Time series plots of the sovereign CDS spreads

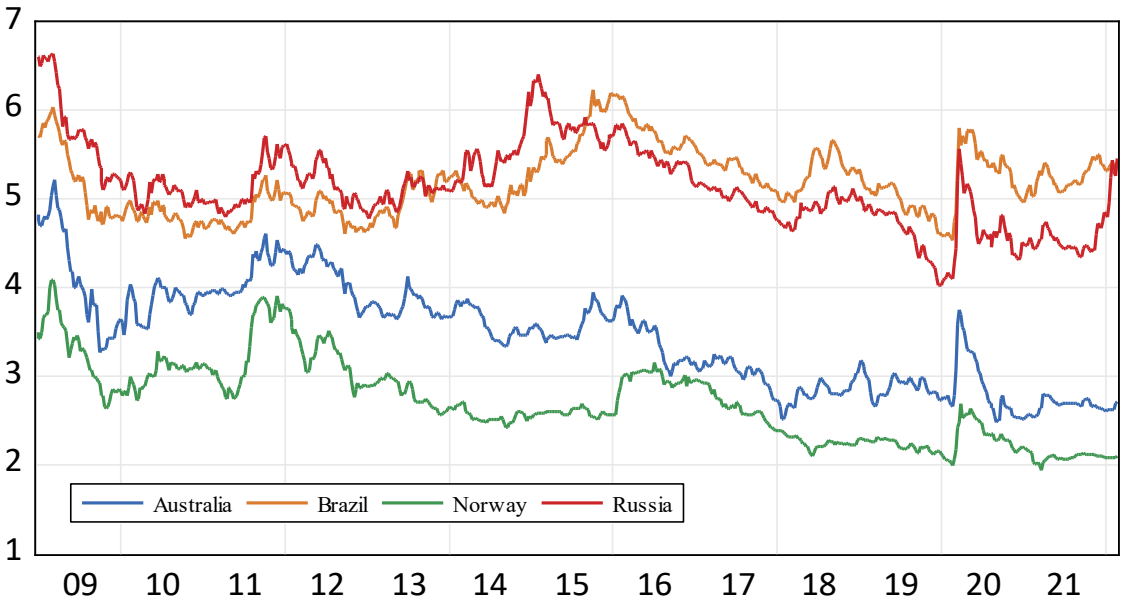


Figure 4.2 FTP smoothed probabilities of the crisis state

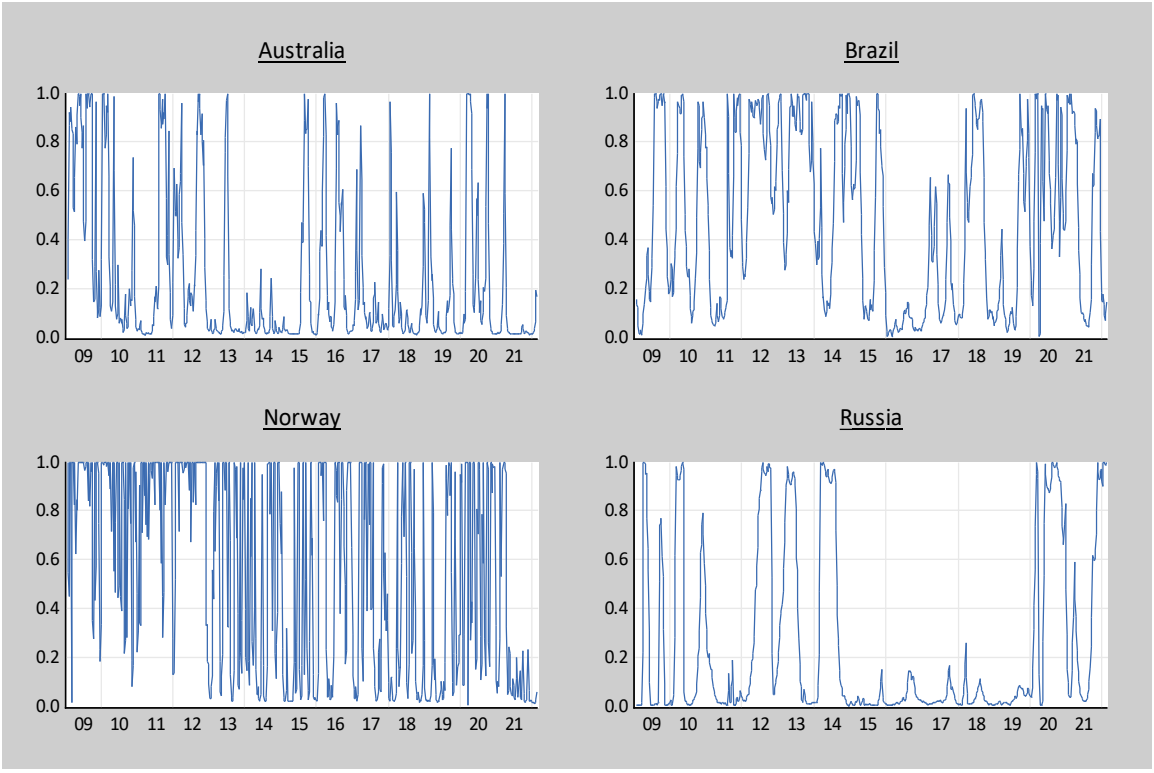
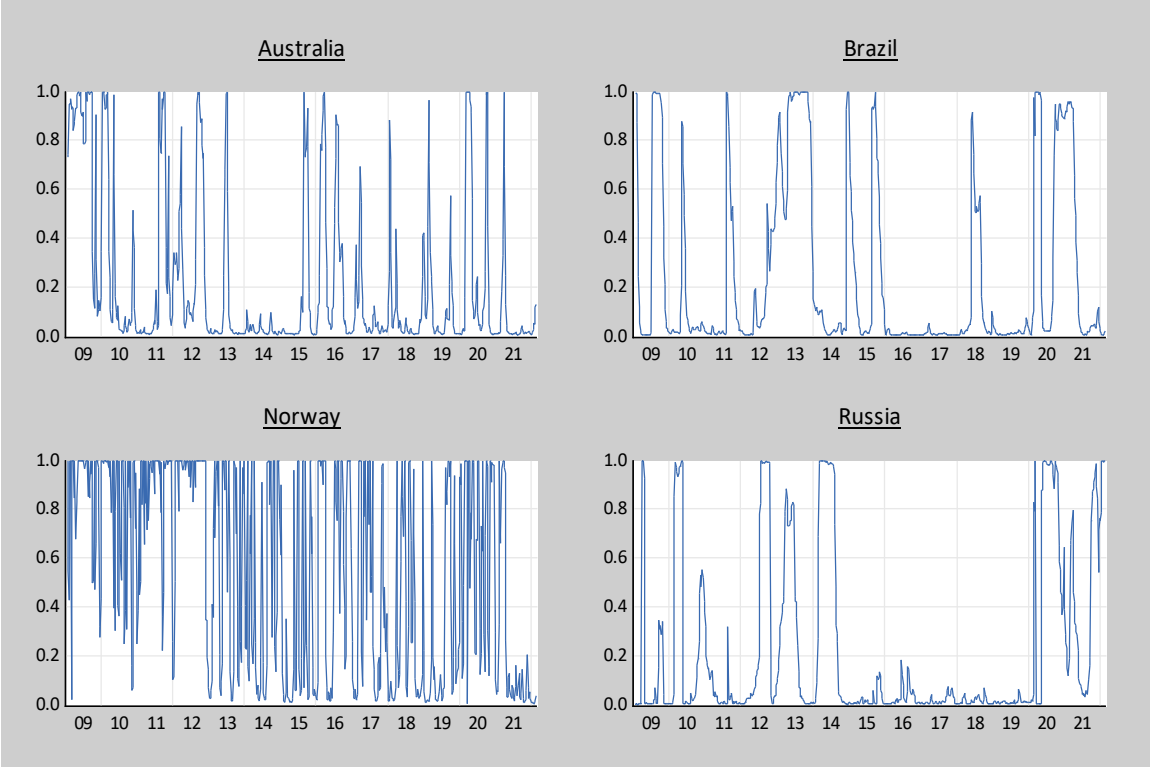


Figure 4.3 TVTP smoothed probabilities of the crisis state



4.8 Appendix C

C.1 Credit default swap valuation

We briefly discuss the discrete-time modelling approach for CDS valuation described in Doshi et al. (2017) and Doshi et al. (2018).[46] A stopping time has an intensity process $\lambda(t)$. If there is no default up to time t, the probability of no default occurring in the next interval is $exp(-\lambda(t))$. We let τ denote the random default time for the sovereign, that is, a stopping time generated by the default process $N_t = 1_{\tau \geq t}$. Under the risk-neutral measure Q, the probability of a sovereign surviving until at least k periods conditional on no default up until time *t* is given by

$$E_t^Q[1_{\tau>t+k}] = E_t^Q\left[exp\left(-\sum_{j=0}^{k-1}\lambda_{t+j}\right)\right], \tag{4.17}$$

where $1_{\tau>t+k}$ is an indicator function that is equal to 1 if a default event occurs after time $t+k$, and 0 otherwise. The default intensity for an obligor is assumed to be a quadratic function of state variables relevant to credit risk, which consist of $X_{z,t}^g$ global variables and $X_{z,t}^d$ country-specific factors. Thus

$$\lambda_t = \left(\alpha_0 + \sum_{z=1}^{n}\alpha_z^g X_{z,t}^g + \sum_{z=1}^{m}\alpha_z^d X_{z,t}^d\right)^2, \tag{4.18}$$

where n is the number of global factors and m is the number of country-specific factors. The quadratic specification has the advantage that the intensity function is strictly positive.

Let *S* denote the CDS spread, and Δ denote the time period between payment dates, so that $S\Delta$ is the periodic payment conditional on no default by the reference entity. In the event of a default before maturity, the protection buyer receives a payment of $(1-R)$ per dollar of the notional from the protection seller, and the contract terminates. *R* is the recovery rate so that $1-R$ is the loss given default (LGD), which the CDS insures. The present value of the payments by the protection buyer is given by:

[46] See Doshi et al. (2018) for a more detailed discussion of the framework.

$$PB(t,t+k) = E_t^Q\left[S\Delta * \exp\left(-\sum_{j=0}^{k-1} r_{t+j}\right) * 1_{(\tau>t+k)}\right] \tag{4.19}$$

$$= S\Delta * E_t^Q\left[\exp\left(-\sum_{j=0}^{k-1} r_{t+j} + \lambda_{t+j}\right)\right].$$

We assume that the recovery rate is known and that if a default event occurs in the time interval $(t+k-1, t+k)$, the protection seller makes the payment LGD_{t+k-1}. The present value of this cash flow by the protection seller is given as

$$PS(t,t+k) = E_t^Q\left[LGD_{t+k-1} * \exp\left(-\sum_{j=0}^{k-1} r_{t+j}\right) * 1_{(\tau>t+k-1)}\right]$$
$$-E_t^Q\left[LGD_{t+k-1} * \exp\left(-\sum_{j=0}^{k-1} r_{t+j}\right) * 1_{(\tau>t+k)}\right]. \tag{4.20}$$

If split into two components, we obtain

$$PS(t,t+k) = E_t^Q\left[LGD_{t+k-1} * exp\left(-\sum_{j=0}^{k-1} r_{t+j}\right) * exp\left(-\sum_{j=0}^{k-2} \lambda_{t+j}\right)\right]$$
$$-E_t^Q\left[LGD_{t+k-1} * \exp\left(-\sum_{j=0}^{k-1} r_{t+j}\right) * exp\left(-\sum_{j=0}^{k-1} \lambda_{t+j}\right)\right]. \tag{4.21}$$

The CDS spread level is set such that the present value of the payments by the protection buyer is equal to the present value of the protection seller, that is

$$\sum_{k=1}^{T/\Delta} PB(t,t+k\Delta N) = \sum_{h=1}^{N\times T} PS(t,t+h), \tag{4.22}$$

where *N* is the number of trading days in a year, Δ denotes the time period between payment dates, and *T* refers to the CDS contract maturity in years.

C.2 Quantile regressions

The theoretical quantiles $Q_Y(\tau)$, $\tau \in (0,1)$ of a random variable Y are defined as:

$$P(y \le Q_Y(\tau)) \ge \tau \quad \text{and} \quad P(y \ge Q_Y(\tau)) \ge 1-\tau, \tag{4.23}$$

that is, τ is the probability of observing a realisation below (or equal to) $Q_Y(\tau)$ while $1-\tau$ is the probability of a realisation above (or equal to) $Q_Y(\tau)$.The conditional quantile function

of Y given X is the inverse of the corresponding conditional cumulative distribution function, that is,

$$Q_Y(\tau|X) = F_Y^{-1}(\tau|X) = inf\{y: F_Y(y|X) \geq \tau\} \tag{4.24}$$

where $F_Y^{-1}(\tau|X) = P(Y \leq y|X)$. The conditional quantile function provides a complete description of the whole conditional distribution. Considering a random variable Y with a distribution function $F(y)$, the τ-th quantile of Y is defined by

$$Q_Y(\tau|X) = inf\{y|F(y) \geq \tau\}. \tag{4.25}$$

With a random sample $\{y_1, \dots, y_n\}$ from the cumulative distribution function $F(y)$ such that $0 \leq F(y) \leq 1$ is by construction a non-negative function, the τ-th sample quantile can be defined as

$$\hat{Q}_Y(\tau|X) = inf\{y|\hat{F}(y) \geq \tau\}. \tag{4.26}$$

where $\hat{F}$ is the empirical distribution function of the random sample.

Let us consider the standard linear regression model taking the form

$$Y_t = \beta' X_t + u_t \tag{4.27}$$

where X_t is a vector of k predictors (also including the lags of the dependent variable) plus the intercept term, and u_t is an independent and identically distributed ($i.i.d.$) sequence of mean-zero random variables with distribution function $F(\cdot)$. Then the conditional distribution of Y_t is a location shift of $F(\cdot)$, with conditional mean $\beta' X_t$.

Thus, with quantile regression, the τ-th conditional quantile of Y_t is a linear function of X_t, that is,

$$Q_{Y_t}(\tau|X_t) = \beta' X_t + F_u^{-1}(\tau) = \beta(\tau)' X_t, \tag{4.28}$$

where $\beta(\tau)' = (\beta_1 + F_u^{-1}(\tau), \beta_2, \dots, \beta_k)$. Koenker and Bassett (1978) show that the τ-th conditional regression quantile can be estimated by:

$$\hat{Q}_{Y_t}(\tau|X_t) = \hat{\beta}(\tau)' X_t \tag{4.29}$$

where the regression slopes $\hat{\beta}(\tau)$ are obtained by minimising the quantile-weighted absolute value of errors:

$$\hat{\beta}(\tau) = \underset{\beta \in R^k}{arg\,min} \left[\begin{array}{l} \sum_{t \in \{t: y_t \geq x_t \beta\}} \tau \left| y_t - \beta(\tau)' x_t \right| \\ + \sum_{t \in \{t: y_t < x_t \beta\}} (1-\tau) \left| y_t - \beta(\tau)' x_t \right| \end{array} \right]. \quad (4.30)$$

Let $\rho_\tau(u) = u\big(\tau - I(u < 0)\big)$, a non-differentiable quantile weighted loss function, then

$$\hat{\beta}(\tau) = \underset{\beta \in R^k}{arg\,min} \sum_t \rho_\tau(y_t - \beta(\tau)' x_t). \quad (4.31)$$

The check function $\rho_\tau(u)$ replaces the traditional quadratic loss used for mean regression. Optimisation of the loss function is done using linear programming methods.

Goodness-of-fit is evaluated using the pseudo-R^2 estimator developed by Koenker and Machado (1999). This estimator is interpreted similarly to the coefficient of determination (R2) derived from OLS regressions. Following Davino et al. (2013), for each analysed quantile τ, the residual absolute sum of weighted differences between the observed dependent variable and the estimated quantile conditional distribution is expressed as follows:

$$RASW = \left[\sum_{t \in \{t: y_t \geq x_t \beta\}} \tau \left| y_t - \beta(\tau)' x_t \right| + \sum_{t \in \{t: y_t < x_t \beta\}} (1-\tau) \left| y_t - \beta(\tau)' x_t \right| \right] \quad (4.32)$$

The total absolute sum of weighted differences between the observed dependent variable and the estimated quantile for the considered quantile τ is given by:

$$TASW = \left[\sum_{t \in \{t: y_t \geq x_t \beta\}} \tau \left| y_t - Q_{Y_t}(\tau) \right| + \sum_{t \in \{t: y_t < x_t \beta\}} (1-\tau) \left| y_t - Q_{Y_t}(\tau) \right| \right] \quad (4.33)$$

where $Q_{Y_t}(\tau)$ is a model with only the intercept. The *pseudo*R^2, lying between 0 and 1, can be computed as follows:

$$pseudoR^2 = 1 - \frac{RASW}{TASW} \quad (4.34)$$

The *pseudo*R^2 measure is defined at a given quantile, hence it cannot be considered a measure of the goodness of fit of the whole model.

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5 Conclusion

This thesis comprises three chapters, each focusing on a distinct area. This chapter concludes by presenting the key findings and contributions, addresses limitations, and provides recommendations for future research endeavours. Our research will interest a wide range of readers.

5.1 Key Findings, implications, and future research

Chapter 2 examines the implications of shocks to global variables (global economic activity, global financial conditions, and global commodity prices) for economic and stock market performance in advanced and emerging economies that are heavily reliant on commodity exports. A dependency on commodity exports can present immense opportunities for resource-rich economies when managed effectively. Commodity exports generate revenues, fiscal benefits, employment, and infrastructure development, positively impacting GDP. Norway, an energy-exporting developed economy, and Chile, a predominantly metal-exporting emerging economy, exemplify a well-managed use of natural resource wealth. They have established sovereign wealth funds and strong institutional and policy frameworks to address commodity price fluctuations. They are viewed as the *poster children* for other resource-dependent economies, demonstrating that if commodity exposure is effectively managed, the economy can greatly benefit from its natural resource wealth. However, the literature also highlights significant challenges associated with commodity dependence, including poor governance, volatile macroeconomic conditions, and the Dutch disease phenomenon. A decline in export prices leads to significant foreign-exchange losses, which can constrain policy space and hinder capital formation.

The chapter considers Australia, Brazil, Chile, New Zealand, Norway, Russia, and South Africa. We demonstrate that an increase in global economic activity, which raises global demand, eases global financial conditions, and raises commodity export prices, has significant expansionary effects on the economic output of both emerging and developed countries, with the notable exception of New Zealand. Global activity shocks are also positively related to stock market performance, with significant effects particularly in

developed economies (except New Zealand). A deterioration in global financial conditions is estimated to lower global economic conditions and commodity export prices. While we do not find significant contractionary effects of global financial risk shocks on domestic output across the countries (except Brazil), they have highly significant negative effects on stock market performance in all countries. Commodity (specific) price shocks generally have immaterial effects on output, while the effects on stock market performance are briefly significant following the impact.

This implies that a slowdown in the global economy, which heightens global financial risks and lowers commodity prices, could reduce domestic economic output and negatively affect stock market performance. Such an environment harms investor sentiment, diminishes household wealth, decreases consumption expenditure, and limits firms' access to capital, resulting in lower investment, wages, and employment. This finding aligns with several studies showing that global economic activity is the dominant driver of commodity prices and significantly affects the macroeconomies of exporters in particular. Both emerging and developed economies can adopt macroprudential regulation, which, if optimally managed, can mitigate the negative effects of tightened global financial conditions on the economy (Sandri, 2020).

Chapter 2 relied on country-specific structural vector autoregression (SVAR) models. Future research employing panel data methods, which increase statistical power, could also provide valuable insights. The SVAR models used several dummy variables to address outliers, thereby reducing residual autocorrelation and stability issues. A Markov-switching SVAR framework that allows the coefficients and variances of endogenous variables to depend on the state could also improve understanding of the effects of global shocks by capturing nonlinear relationships, structural breaks, and volatility changes (heteroskedasticity). Further analyses could likewise explore the impact of global shocks on exchange rates and sovereign yields in commodity-export-dependent countries.

The second essay (Chapter 3) evaluates the vulnerability of US investment-grade corporate credit spreads to economic growth risks. We calculated three measures of industrial production growth risk: downside risk (growth-at-risk), uncertainty, and skewness, which reflects the imbalance between downside and upside risks. These three risk measures add explanatory power for AAA- and BBB-rated credit spreads beyond the factors identified in previous studies. Our findings reveal that the BBB-rated segment of the investment-grade bond market is highly sensitive to macroeconomic tail risks and increased uncertainty. This indicates a greater chance of downgrades to the bond market's speculative-grade segment

during severe economic downturns. Such widespread downgrades can trigger forced bond sales by institutional investors (e.g., pension funds), cause widespread disruptions across credit and equity markets, and lead to higher borrowing costs and limited access to funding, particularly for highly leveraged firms. As Albuquerque et al. (2025) discuss, in the current environment of elevated corporate debt and rising interest rates, continuous monitoring of corporate sector risks, along with the development and implementation of policies to manage them, is vital.

Future research can extend the framework to investigate how tail risks and uncertainty in other macroeconomic variables, such as inflation and unemployment, influence corporate credit markets. Other advanced and emerging economies could also be considered. As the relationship between credit spreads and macroeconomic risks may differ across various economic regimes, future studies should explore the regime-dependent effects of macroeconomic risks on corporate credit risk.

The third essay (Chapter 4) examines potential regime dependence in the effects of commodity prices on sovereign credit risk in countries that rely heavily on commodity exports, including Australia, Brazil, Norway, and Russia. We use sovereign credit default swaps (CDS) as our measure of sovereign credit risk. Through Markov-switching regression analysis, we identify crisis and non-crisis regimes within the sovereign CDS markets. Results show that rising commodity prices significantly decrease sovereign CDS spreads in both crisis and non-crisis regimes for Australia, Brazil, and Russia. Notably, Norway's credit risk remains unaffected by fluctuations in commodity prices during non-crisis periods, suggesting that adverse commodity market shocks have little impact on its creditworthiness during tranquil states. Among the countries studied, Norway exhibits the lowest sensitivity to global commodity price changes during both crisis and non-crisis periods, whereas Russia's CDS spreads are the most sensitive. The literature indicates that Norway is distinct in having a sovereign wealth fund largely funded by commodity revenues, which helps manage its revenues. Additionally, it implements fiscal rules to regulate government expenditure of the fund's earnings. Australia maintains a sovereign wealth fund (SWF) that is not based on commodity revenues. Brazil and Russia have established SWFs, some of which have since ceased operations.

The findings of the chapter suggest that a decline in commodity prices can significantly widen the sovereign CDS spreads of countries that depend on commodity exports, especially those with low credit ratings. This may lead to a deterioration in credit quality, which often results in lower bond prices and higher borrowing costs for

governments. Market participants might interpret this as an early sign of increased economic, political, and fiscal uncertainty, causing reduced bond market liquidity, higher yields, and weakened fiscal and financial stability.

Further research could consider the 10-year sovereign yield spread as an alternative measure of credit risk to examine the state-dependent and asymmetric behaviours in response to fluctuations in commodity prices. It would also be interesting to analyse the implications of fluctuations in sectoral commodity indices (such as energy, agriculture, and metals) for sovereign credit risk. Future studies might extend the analysis to advanced and emerging economies that are heavily dependent on commodity imports.

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