Trading Activity, Financial Intermediation, and Price Formation in Foreign Exchange Markets

by

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Abstract

This thesis investigates how trading activity, financial intermediation, and dealer balance-sheet frictions jointly shape price formation in foreign exchange (FX) markets. This thesis uses proprietary bilateral over-the-counter (OTC) datasets from two of the world's largest foreign exchange dealer banks to construct a unified framework, which links micro-level trading dynamics with intermediate asset pricing theory. The analysis is divided into three interconnected empirical sections. Each section builds on the previous one, progressively discussing how trading volume, order flow, and dealer constraints interact to determine exchange rate dynamics.

Chapter 2 examines the relationship between trading volume, order flow, and volatility in FX markets by using weekly data on twelve currencies from 2001 to 2012. The analysis employs both realised volatility proxy and implied volatility. The results confirm a robust positive volume–volatility relationship across most currency pairs, which is consistent with information-based trading models. However, a portfolio-sorting approach reveals that this relationship is state-dependent. When trading volume increases, its marginal impact on volatility decreases. This result suggests that high-volume periods are dominated by non-informational activity such as liquidity provision and inventory adjustment. Introducing directional order flow adds substantial explanatory power. Portfolios characterised by strong buying pressure exhibit significantly positive volatility coefficients, while those with selling pressure show negative coefficients. This indicates an asymmetric information channel. Disaggregating order flow by customer type shows heterogeneity: retail (private client) order flow generates a volatility impact five to seven times larger than institutional flow, despite accounting for only 10–2% of total volume. These findings suggest that, compared to total trading

volume, trading direction and trader identity are also major drivers of foreign exchange volatility.

Chapter 3 shifts the focus to the predictive content of FX trading volume for exchange rate returns and introduces dealer balance-sheet constraints as the key conditioning variable. This chapter uses unique data from two dealers to demonstrate that trading volume can predict subsequent USD appreciation. However, this predictive ability is limited to the period after the crisis, and only under balance sheet constraint. Before the 2008 crisis, the same volume carried no predictive content. This structural break is documented using three proxies for balance-sheet stress: the CDS spreads, intermediary leverage, and the LIBOR-OIS spread. We sort the sample by the median of each proxy yield and get a consistent result: volume predicts returns exclusively during high-constraint periods. These findings challenge the prevailing view that FX volume predictability arises primarily from asymmetric information.

Chapter 4 identifies and explains the supply-demand mechanism through which dealer balance-sheet frictions affect price formation. The chapter directly estimates the slope of the US dollar supply curve by interacting normalised volume with dealer CDS spreads. The results show that the supply curve steepens sharply during periods of balance-sheet stress. This implies that, with limited intermediary capacity, the same level of trading pressure will produce a larger exchange rate response. Event-time analyses around CDS shocks confirm that FX prices respond to trading pressure when both balance-sheet constraints and trading volume are jointly elevated. On the demand side, the chapter documents that surges in dollar demand during crises originate primarily from leveraged financial clients. Their trading was highly sensitive to the dealers' capital situation, while the cash flows of non-financial clients were unrelated to the dealers' capital. This interaction between capital-dependent demand and a steep supply curve lead the positive correlation between foreign exchange trading volume and subsequent dollar appreciation after periods of crisis.

In summary, this thesis makes three contributions. First, it provides comprehensive evidence that the volume–volatility relationship in FX markets is positive. And it is driven by trade direction and trader heterogeneity rather than aggregate volume alone. Secondly, it confirms that foreign exchange trading volume contains predictive information about prices, and this is a mechanistic consequence of the post-crisis balance sheet constraints. Third, it points out that debt overhang makes the dollar supply curve steeper and the demand curve rise, thereby amplifying the impact of trading activity on prices. These findings have implications for exchange rate modelling, risk management, and financial stability policy. This thesis suggests that monitoring dealer balance-sheet health is essential for understanding FX market dynamics.

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Dedication

"For my mom,

Thank you for lifting me with all your strength so that I could see a wider sky.

I wish you could have seen this view too. "

"妈妈, 谢谢你用尽全力的托举，让我得以望见更广阔的天空。"

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Declaration

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

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Chapter 1

Introduction

The foreign exchange (FX) market is the largest financial market in the world. According to the 2022 Bank for International Settlements Triennial Survey, average daily trading volume exceeded 7.5 trillion US dollars (Drehmann and Sushko (2022)). Despite this scale, how trading activity translates into prices in this market remains an open question. The classical answer comes from information-based microstructure theory. Kyle (1985) shows that informed traders generate price impact through strategic order submission, and Glosten and Milgrom (1985) shows that market makers revise quotes in response to trade direction under asymmetric information. On this view, trading activity proxies for the arrival of information, an interpretation supported by the robust positive correlation between trading volume and volatility documented across asset classes (Karpoff (1987)). In currency markets, Evans and Lyons (2002) establish that order flow explains a substantial share of exchange rate variation, and Lyons (2001) develops the dealer-based framework in which dispersed private information is aggregated into prices through customer and inter-dealer trading.

A common feature of this literature is that the mapping from trading activity to prices is treated as stable. Dealers are assumed to supply liquidity elastically, so a given trade produces the same price response regardless of the financial condition of the intermediaries who absorb it. Intermediary asset pricing theory questions this assumption. He and Krishnamurthy (2013) and Adrian et al. (2014) show that the capital and leverage of financial intermediaries act as state variables that govern risk-bearing capacity and asset prices, and He et al. (2017) document that a capital ratio constructed from primary dealer balance sheets prices the cross-section of returns in several asset classes, including currencies. These considerations carry particular weight in FX, where a small number of large dealer banks intermediate the vast majority of spot transactions. If dealer balance sheets matter, the informativeness and the price impact of FX trading activity should not be structural constants. They should vary with the state of the intermediary sector. Whether they do, and through which mechanism, is the question this thesis addresses.

The analysis draws on two proprietary bilateral over-the-counter (OTC) datasets obtained from two of the largest global FX dealers. The first records weekly trading volume and matched customer order flow for eleven currencies against the US dollar from 2001 to 2012, a sample that spans the Global Financial Crisis. The second records daily volume and order flow for the G9 currencies from 2018 to 2021, disaggregated by client type, and captures the COVID-19 shock. Unlike the settlement-based aggregates used in much of the recent literature, these data measure customer-level trading from the dealers' own books. They also permit a comparison across two independent dealers, two distinct regimes, and two major crises. The thesis is organised as three interconnected empirical chapters. Chapter 2 establishes the basic relationships between volume, order flow, and volatility. Chapter 3 shows that the predictive content of volume for exchange rate returns is conditional on dealer balance-sheet stress. Chapter 4 identifies the supply and demand mechanism that generates this conditionality.

Chapter 3 examines the volume and volatility relationship using weekly data on twelve currencies from 2001 to 2012 and both realised and implied volatility measures. Across most currency pairs, trading volume is positively related to volatility, consistent with evidence from equity markets. Portfolio sorts reveal, however, that the relationship is state-dependent. The marginal effect of volume on volatility declines as trading intensity rises, which suggests that high-volume periods are dominated by non-informational activity such as liquidity provision and inventory adjustment. Introducing directional order flow adds substantial explanatory power. Portfolios characterised by buying pressure carry significantly positive volatility coefficients while portfolios characterised by selling pressure carry negative coefficients, and the coefficients rise monotonically across the order flow distribution. Disaggregating flow by client type reveals pronounced heterogeneity. Order flow from private clients generates a volatility impact five to seven times larger than institutional flow despite accounting for only 10 to 20 percent of total volume, while corporate hedging flows can dampen volatility. Trade direction and trader identity, rather than aggregate volume alone, are therefore the primary drivers of FX volatility.

Chapter 4 turns to the predictive content of FX trading volume for currency returns. Recent work interprets volume predictability as evidence of asymmetric information and demand-side learning (Cespa et al. (2022a)). If that interpretation is correct, predictability should appear in any period with informed trading, including the years before 2008. The chapter shows that it does not. FX spot dollar volume predicts subsequent US dollar appreciation only after 2008, and within the post-crisis sample only when dealer balance-sheet constraints are tight. Before the crisis the same volume carries no predictive content. The chapter documents this structural break using three proxies for balance-sheet stress: the average five-year CDS spread of the largest dealer banks, the intermediary leverage measure of He et al. (2017), and the LIBOR-OIS spread. Sorting the sample by the median of each proxy yields a consistent result, namely that volume predicts returns exclusively during high-constraint periods. The pattern holds across both dealers and both crises, and it is difficult to reconcile with a purely information-based explanation. The post-crisis rise in dealer funding costs, driven in part by regulatory changes such as the Dodd-Frank Act and by persistently elevated credit spreads (Berndt et al. (2024)), points instead to a supply-side friction.

Chapter 5 identifies that friction. Building on the theory of debt overhang (Myers (1977); Andersen et al. (2019)), it argues that when dealer leverage is high, expanding the balance sheet transfers value from equity holders to creditors, so equity holders demand greater compensation to intermediate. The consequence is not quantity rationing but worse pricing. Constrained dealers continue to trade, but the supply curve for dollar liquidity steepens. The chapter estimates the slope of the dollar supply curve directly by interacting normalised volume with dealer CDS spreads and finds that the slope rises sharply during the 2008 crisis and the COVID-19 shock while remaining flat in normal times. Event-time analyses around CDS shocks show that exchange rates respond to trading pressure only when balance-sheet constraints and trading volume are jointly elevated, with no pre-trends and no comparable response outside that joint state. On the demand side, surges in dollar buying during crises originate primarily from leveraged financial clients whose trading is sensitive to dealer capital, while non-financial client flows are unrelated to it. A simple model of FX spot intermediation with debt overhang and capital-dependent demand rationalises these facts and delivers the joint-state prediction that the data confirm.

The thesis makes three contributions. First, it provides comprehensive evidence that the positive volume and volatility relationship in FX markets is driven by trade direction and trader heterogeneity rather than by aggregate volume, and that the relationship weakens precisely when trading is most intense. Second, it establishes that the predictive content of FX volume is not a structural feature of the market but a regime-dependent outcome conditioned on dealer balance-sheet frictions. Third, it identifies the mechanism. Debt overhang steepens the dollar supply curve while capital-dependent demand from leveraged clients shifts the demand curve, and the interaction of the two amplifies the price impact of trading activity. Together these results connect the microstructure literature on trading and volatility with the intermediary asset pricing literature, and they attribute the state dependence observed in the former to the frictions studied in the latter.

The findings have implications for exchange rate modelling, for risk management, and for policy. Models that treat the price impact of order flow as constant will understate volatility when dealers are stressed and overstate it in normal conditions. Volume-based trading signals should not be extrapolated to periods of low balance-sheet stress, and monitoring dealer health through CDS spreads, leverage, and funding spreads is essential for judging when such signals are informative. For central banks, the results imply that FX markets become fragile when dealer balance sheets are impaired, and that the effectiveness of intervention depends on the state of intermediary constraints (Ferreira et al. (2024)). The remainder of the thesis proceeds as follows. Chapter 2 reviews the literature on trading activity, order flow, intermediary constraints, and debt overhang, and situates the three empirical chapters within it. Chapters 3 to 5 present the empirical analysis. Each chapter is self-contained, with its own data description, methodology, and robustness tests.

Chapter 2

Literature Review

2.1 Trading Activity, Information, and Price Formation

Financial markets incorporate information through trading rather than instantaneously through public signals. In foundational microstructure models, prices adjust as order flow reveals private information and redistributes risk. Kyle (1985) formalizes how informed trading generates price impact through strategic order submission. Glosten and Milgrom (1985) show that asymmetric information leads market makers to update prices based on trade direction. Inventory-based models further emphasize that liquidity suppliers adjust prices to manage risk from absorbing order imbalances. These three channels: strategic informed trading, adverse selection, and inventory management, are not mutually exclusive and may collectively influence price formation.

In decentralised markets like foreign exchange, these mechanisms are amplified, with traders acting as intermediaries between different customer flows and managing inventory across currencies. A defining characteristic of FX markets is the absence of a centralized order book to aggregate information. Instead, information is dispersed among heterogeneous participants including central banks, financial institutions, multinational corporations, and speculative traders (King et al. (2013)). Each group operates based on distinct knowledge, objectives, and risk tolerances. In this fragmented market structure, order flow serves as the primary mechanism through which dispersed private signals are incorporated into exchange rates, rather than merely acting as a proxy for information arrival. Rime et al. (2010) provides empirical confirmation for this channel, demonstrating that order flow retains substantial explanatory power for exchange rate variation even after controlling for macroeconomic news.

The decentralized structure of the foreign exchange market suggests that the informational content of order flow depends on the identity of the trader. Consequently, aggregating all transactions into a single metric of trading activity may obscure significant heterogeneity. A comprehensive understanding of how trading transmits information to prices therefore requires accounting for both the volume and the specific source of the trades.

However, most models abstract from intermediary balance-sheet constraints, such as leverage, funding costs, and capital constraints. For this reason, the mapping from trading activity to price impact is often treated as stable. This assumption is increasingly difficult to sustain in light of recent empirical evidence. Ranaldo and de Magistris (2022) investigate the price impact of trading volume in the global FX market using a decade of CLS intraday data and demonstrate that market depth is not constant. Instead, depth varies systematically with transaction costs, money market stress, and aggregate uncertainty. When funding conditions tighten and risk aversion rises, a given unit of order flow generates a larger price impact. This shift does not necessarily reflect a change in the informational content of the trade but rather a diminished capacity of intermediaries to absorb it.

Such evidence suggests that the transmission of trading activity into price dynamics consists of two distinct components. The first is the informational signal embedded in the trade, and the second is the willingness and ability of dealers to warehouse the resulting inventory. While the microstructure literature has thoroughly developed the former, the latter remains comparatively under-explored, particularly within the specific context of foreign exchange markets.

Chapter 3 builds directly on this microstructure foundation by examining how volume and order imbalance relate to volatility. Chapter 4 departs from the frictionless intermediation assumption and introduces intermediary constraints as a determinant of price impact.

2.2 The Volume–Volatility Relationship

A long empirical tradition documents a strong positive relationship between trading volume and volatility across asset classes. Several theoretical interpretations exist.

The Mixture-of-Distributions Hypothesis (Clark (1973)) proposes that both volume and volatility respond to latent information arrival. Sequential information models (Copeland (1976)) argue that heterogeneous beliefs lead to bursts of trading and volatility. Inventory-based theories suggest that larger order imbalances force market makers to adjust prices more aggressively. Each of these explanations treats volume as an aggregate indicator of underlying market conditions and predicts a positive volume–volatility correlation. As Su et al. (2010) note, this relationship has consequently become a standard benchmark for assessing market efficiency and the informational role of trading activity.

However, the vast majority of this evidence originates from equity and derivatives markets. Evidence from foreign exchange markets is comparatively sparse and reveals additional complexities. Galati (2000) provide early FX-specific evidence using BIS data on seven emerging market currencies. They find a positive correlation between unexpected volume and volatility that is broadly consistent with the Mixture of Distributions Hypothesis. Notably, this correlation weakens or even reverses during episodes of extreme volatility. Such a pattern is not predicted by standard theoretical frameworks and suggests that the volume–volatility link may be state-dependent.

Chuang et al. (2009) explore the causal direction and find evidence of bidirectional Granger causality between FX volume and volatility, which complicates the interpretation that volume serves as a simple proxy for information arrival. Giot et al. (2010) and Malinova and Park (2010) extend the analysis using higher-frequency data and confirm the positive association but provide limited insight into the underlying drivers.

More recently, Cespa et al. (2022a) adopt a fundamentally different approach. Using CLS settlement data, they decompose foreign exchange trading volume into components related to volatility, liquidity, and order flow. They demonstrate that only the residual portion of trading volume—the part unexplained by these variables—predicts currency returns for the following day. This finding suggests that foreign exchange trading volume contains information far beyond what a simple volume–volatility correlation can capture. It likely reflects the degree of information asymmetry among market participants while indicating that a large portion of volume represents non-informative activity.

These findings raise the question of whether the informational content of aggregate volume can be sharpened by considering the direction or source of trading. Several lines of evidence support this possibility. Chan and Fong (2000) demonstrate that incorporating order imbalance alongside volume improves the explanation of the volume–volatility relationship in FX markets, which suggests that the signed component of trading carries information that unsigned volume obscures. Malinova and Park (2010) provide a theoretical rationale for this link. They argue that as trading volume increases, a greater number of participants trade in the direction of arriving information, thereby amplifying order imbalance and driving volatility.

The composition of traders is also a critical determinant of market dynamics. Daigler and Wiley (1999) seperate futures trading volume by trader type and find that the positive volume–volatility relationship is driven primarily by non-member public trading. In contrast, floor trader activity is negatively associated with volatility. This pattern is consistent with the hypothesis that professional intermediaries absorb rather than generate volatility.

In equity markets, recent research focuses on the destabilizing role of retail investors. Eaton et al. (2022) exploit brokerage platform outages as exogenous shocks to show that reduced retail participation leads to lower volatility and improved liquidity, thereby establishing a causal link between retail trading and market instability. Baig et al. (2022) further demonstrate that this destabilizing effect intensifies during crisis periods such as the COVID-19 pandemic. Do similar dynamics apply to the foreign exchange market? Although retail participants account for a small share of trading in the foreign exchange market, their influence may not be negligible. This remains a question that requires empirical research. This paper addresses this issue directly by disaggregating order flow across asset managers, corporate clients, hedge funds, and private clients.

Despite robust evidence, this literature generally treats volume as an aggregate indicator and abstracts from the financial health of intermediaries. Liquidity supply is implicitly assumed to be sufficiently elastic.

Chapter 3 extends this literature to FX markets by using both realised and implied volatility; Normalizing volume across currencies; Including order imbalance measures; Examining cross-sectional heterogeneity; and conducting portfolio-based tests and robustness exercises.

This establishes that trading activity–volatility relationships are strong and systematic in currency markets. But the existing microstructure literature does not explain why the strength of the volume–volatility link varies across states (shock and non-shock periods). This gap motivates Chapter 4.

2.3 Volatility Measurement and Risk Expectations

Volatility can be measured ex post using return variability or ex ante using implied volatility from option prices. High-frequency realized volatility estimators provide accurate measures of ex post risk. Implied volatility embeds risk-neutral expectations and risk premia (Christensen and Prabhala (1998)).

The difference between these two metrics is substantial, not merely methodological. If a change in order flow affects realized and implied volatility in the same direction and magnitude, it suggests a persistent shift in the information environment and a revised market assessment of underlying uncertainty. Conversely, if realized volatility responds more strongly than implied volatility, the effect is likely a temporary phenomenon. In this scenario, prices are driven by short-term demand pressure rather than a fundamental reassessment of risk.

Hendershott and Menkveld (2014) shows this distinction in the context of institutional trading. They argue that buying pressure can generate a transient price impact that raises realized volatility without proportionally increasing expected future volatility. This pattern is particularly informative when combined with trader-type analysis. Pojarliev and Levich (2010) document that hedge fund trading strategies often generate short-term realized volatility through aggressive directional positions while simultaneously reducing forward-looking uncertainty by accelerating the incorporation of information into prices.

Corporate hedging flows operate through a different channel. Allayannis and Ofek (2001) show that firms hedge currency exposure to reduce earnings variability. This implies that corporate order flow is designed to dampen rather than amplify volatility in both its realized and expected dimensions.

Using both measures allows Chapter 3 to connect trading activity to realized variability and to forward-looking risk perceptions.

2.4 Order Flow and Exchange Rate Determination

Exchange rate determination differs from equity markets because trading occurs in an OTC dealer network. Dealers absorb customer flows and set quotes. Evans and Lyons (2002) show that order flow explains exchange rate changes because it captures information and demand imbalances. Lyons (2001) develops the formal theoretical framework for this insight. In his model, dealers cannot observe the fundamental value of a currency directly but must infer it from the sequence of customer orders. Because each dealer observes only a fraction of total market activity, the aggregation of dispersed information occurs gradually through inter-dealer trading and quote adjustments rather than instantaneously through a centralized mechanism. This structure implies that the direction of order flow (defined by whether net buying or selling pressure prevails) should be more informative about fundamentals than total trading volume. Direction reflects the balance of beliefs among informed participants, whereas volume conflates information-driven and liquidity-driven trades (Evans and Lyons (2002)).

Empirical research confirms that order flow is not uniformly informative but varies in signal content depending on the participant. Menkhoff et al. (2016) provide direct evidence by decomposing customer order flow from a major FX dealer into client segments. They show that financial customer flows predict exchange rate movements significantly better than commercial or retail flows. Ranaldo and Somogyi (2021) extend this finding to a global scale using CLS data. By estimating the permanent price impact of trades, which represents the component not subsequently reversed, they demonstrate that funds and non-bank financial firms generate more persistent price effects than corporates or banks. This result is consistent with these participants possessing superior information or more directional trading motives. Chordia et al. (2002) document a complementary mechanism in equity markets, where persistent order imbalances facilitate price discovery by revealing the direction of informed trading.

The relationship between order flow and volatility depends not only on the informational content of the flow but also on the specific response of dealers. This interaction is central to the concept of order flow toxicity. Easley et al. (2012) formalize the risk liquidity providers face when trading against counterparties with superior information, noting that a higher probability of informed flow increases adverse selection costs. Glosten and Milgrom (1985) establish the theoretical foundation for the resulting defensive behavior. Market makers widen spreads to compensate for adverse selection risk, with the magnitude of the adjustment depending on their assessment of the toxicity of incoming flow.

In FX markets, toxicity is closely linked to trader identity. Flows from retail and speculative participants present a particular challenge for dealers. Barber and Odean (2000) and Kumar and Lee (2006) document that retail investors are more sentiment-driven and less systematic than institutional participants. Furthermore, De Long et al. (1990) formalize how noise trading creates demand patterns that are decoupled from fundamentals. When dealers cannot distinguish between informed and noise-driven flow, they respond by adjusting prices more aggressively, which increases realized volatility. However, as Hendershott and Menkveld (2014) argue, much of this volatility may represent temporary price pressure rather than a permanent structural shift. This distinction is critical for interpreting the divergence between realized and implied volatility responses documented in the subsequent analysis.

This part link to chapter 4: If dealer balance-sheet capacity varies, the price impact of order flow should be state dependent. Chapter 4 tests whether volume and order flow are more informative when dealers are financially constrained (i.e. introduced balance sheet constraints).

2.5 Dealers, Intermediaries, and Liquidity Supply

Modern asset pricing research emphasizes that financial intermediaries are central to price formation. Dealers supply liquidity and absorb risk, but their capacity depends on leverage, capital, and funding conditions. Brunnermeier and Pedersen (2009) show how funding liquidity and market liquidity interact, generating liquidity spirals. Adrian et al. (2014) show that intermediary leverage predicts asset returns, highlighting state-dependent risk-bearing capacity. He and Krishnamurthy (2013) model how intermediary constraints affect asset prices. These frameworks imply that price impact and volatility are state dependent.

He et al. (2017) extend this line of research by constructing an intermediary capital ratio from primary dealer balance sheets. They demonstrated that the ratio can reflect cross-sectional prices across multiple asset classes, including currencies. Their measure of leverage is directly linked to dealer equity capital. When leverage rises, equity capital declines and the marginal utility of intermediary wealth increases, which creates a state variable that governs the risk-bearing capacity of the financial sector. Adrian et al. (2017) document a related pattern in bond markets, showing that dealers post wider bid-ask spreads and reduce market-making activity when their balance sheets are under pressure. Duffie (2010) provides a theoretical framework for these dynamics through the lens of slow-moving capital. He argues that in over-the-counter markets, capital does not flow instantaneously to where it is most needed. Instead, dealers must commit their own balance sheets to intermediate trades, and their willingness to do so depends on their current financial position. This insight is particularly relevant for FX markets, where a small number of large dealer banks intermediate the vast majority of spot transactions (Krohn and Sushko (2022)).

The post-crisis era provides direct evidence that these constraints bind in practice. Duffie et al. (2023) show that in the US Treasury market, dealers facing balance-sheet pressure post wider bid-ask spreads to reduce customer flows rather than simply withdrawing from the market. Huang et al. (2025) document an analogous pattern in currency markets. Using CLS data from 2014 to 2022, they show that the FX liquidity supply curve is steeper when dealers face tighter constraints as measured by Value-at-Risk limits and funding costs. Consequently, the same unit of trading volume generates a larger price impact when intermediation capacity is scarce. These findings suggest that the relationship between trading activity and price dynamics in FX markets is incomplete without accounting for the supply side of liquidity provision.

Chapter 4 documents that FX volume predictability is conditional on dealer balance-sheet constraints, using CDS spreads, leverage, and the LIBOR-OIS spread as proxies. Chapter 5 identifies the mechanism through which these constraints affect price formation, showing that the dollar supply curve steepens when debt overhang costs rise.

2.6 Intermediary Constraints and Asset Prices

A growing body of research documents these effects across multiple markets and asset classes. He et al. (2022) demonstrates that during the COVID-19 crisis, Treasury bond prices deviated sharply from fundamental values, and these deviations were closely linked to the scarcity of dealer capital. Dealers were unable or unwilling to absorb sudden selling pressure, causing prices to move far beyond the predictions of standard models. Cenedese et al. (2021) apply this logic to foreign exchange markets. They show that currency mispricing relative to no-arbitrage conditions is systematically related to dealer balance-sheet variables. Their results indicate that these mispricings widen precisely when intermediary constraints tighten. This establishes that FX prices are affected by the same financial frictions affecting other asset markets.

The mechanism operates through both external and internal capital markets. Lu et al. (2023) provides evidence that dealer trading desks rely on internal capital markets to fund intermediation activity, particularly during periods of market stress. When the aggregate balance sheet of a bank is under pressure, internal funding becomes more expensive and difficult to obtain. This forces individual desks to economize on capital, thereby reducing their capacity to warehouse risk. Cooperman et al. (2025) documents a related channel by showing that bank funding risk transmits directly to credit supply and asset pricing through reference rate dynamics. These findings imply that dealer constraints are not merely theoretical constructs but operate through observable funding channels that dictate the cost and availability of intermediation.

Regarding FX markets specifically, recent literature provides further evidence on the supply-side dimension of price formation. Czech et al. (2021) study FX option volume and find that the informational content of trading activity varies with market conditions. Kloks et al. (2023) focus on the FX swap market and show that dealer constraints affect the cost of providing liquidity. They point out that these effects are particularly pronounced around quarter-end dates when regulatory reporting requirements become binding. Collectively, these studies suggest that the elasticity of FX liquidity supply is not constant but fluctuates with the financial health of intermediaries.

Chapter 4 extends this evidence to the FX spot market by showing that volume predictability is conditional on intermediary stress. Chapter 5 traces the transmission channel, showing how internal and external funding frictions translate into a steeper dollar supply curve through debt overhang costs faced by equity holders.

2.7 Dollar Funding Constraints and FX Markets

Post-crisis research highlights the importance of global dollar funding. Deviations from covered interest parity reflect balance-sheet constraints (Du et al. (2018b)). Recent studies have expanded this literature by establishing a direct link between intermediary frictions and exchange rate dynamics. Bruno and Shin (2015) demonstrate that global capital flows and the risk-taking behavior of financial intermediaries are driven by dollar funding conditions. When dollar funding tightens, intermediaries will reduce cross-border lending, and this change will be transmitted to exchange rates through financial channels. Du et al. (2018a) document that the US Treasury premium, representing the convenience yield on dollar-denominated safe assets, rises during funding stress. This premium is linked to the demand for dollar liquidity, and its temporal variation aligns with changes in the capacity of intermediaries to supply dollars.

Jiang et al. (2021) formalize this mechanism through a model in which foreign demand for dollar safe assets determines the exchange rate. In their framework, the dollar appreciates when global investors increase their demand for dollar liquidity, while the magnitude of this appreciation depends on the elasticity of dollar supply. When intermediaries face constraints, supply becomes less elastic, and a given increase in demand produces a larger price effect.

Empirical evidence from crisis episodes provides robust support for these theoretical predictions. Ferreira et al. (2024) studied central bank foreign exchange intervention measures and found that the effectiveness of dollar selling operations depends on the balance sheet status of dealers. When FX dealers are constrained and dollar liquidity is scarce, central bank interventions exert a significantly stronger impact on spot exchange rates. This finding suggests a steeper supply curve during periods of intermediary stress. Burnside and Cerrato (2025b) provide further evidence by analyzing CIP violations, showing that such deviations can be rationalized by the debt overhang costs faced by dealer equity holders. The funding costs driving these deviations are identical to those affecting the willingness of dealers to intermediate spot FX transactions. This creates a unified framework where both CIP violations and the state-dependent informativeness of FX volume originate from a common friction: the constrained supply of dollar liquidity by major dealer banks.

These stress episodes coincide with periods when Chapter 4 finds volume to be most predictive. This empirical evidence also supports the argument in Chapter 5 that volume becomes informative when balance sheet constraints kick in.

2.8 Debt Overhang and Dealer Incentives

Theoretical work on debt overhang (Myers (1977)) and capital structure (Admati et al. (2012)) shows that higher leverage alters equity holders' incentives, affecting risk-taking and pricing. Chapter 3 uses CDS spreads as a proxy for debt overhang costs and documents that FX volume predictability is conditional on their severity. Chapter 4 develops this framework further, providing a formal model of how equity-holder incentives translate into the steepening of the dollar supply curve, and offering a structural interpretation of the microstructure evidence in Chapter 3.

In the standard framework, intermediary capital scarcity operates as a state variable that limits the quantity of intermediation or the risk-bearing capacity of dealers. When capital falls below a threshold, constraints bind, intermediation is reduced, and prices adjust. He et al. (2017) and Adrian et al. (2015) capture this logic. The mechanism is essentially one of quantity rationing: scarce capital means less intermediation.

The analysis in Chapter 5 extends this logic by suggesting that capital scarcity does not merely limit the volume of intermediation but also alters the incentives of equity holders. These agents must decide the terms and prices at which they are willing to supply liquidity. Myers (1977) first identified this phenomenon within the context of corporate investment. When a firm is highly levered, expanding the balance sheet transfers value from equity holders to existing creditors. Consequently, equity holders face a private cost of expansion that exceeds the social cost, leading to underinvestment relative to the first-best outcome. Admati et al. (2018) shows that this distortion has a self-reinforcing effect because equity holders of highly leveraged companies resist capital restructuring, which results in the associated gains flowing disproportionately to creditors.

Andersen et al. (2019) apply this framework to dealer intermediation in derivatives markets. They show that funding value adjustments, which dealers charge to clients for providing OTC liquidity, represent wealth transfers from equity holders to creditors. The dealer CDS spread serves as a proxy for the magnitude of this transfer. When CDS spreads increase, the debt overhang wedge widens, and equity holders require greater compensation to expand intermediation activity.

Under the traditional framework, tight constraints lead dealers to stop intermediation or to limit supply. In contrast, the debt overhang view suggests that dealers may continue to intermediate but will do so at higher prices. In this scenario, the liquidity supply curve steepens rather than shifting inward. Trading volume does not necessarily collapse during periods of market stress. Instead, a given volume generates a larger price impact because equity holders demand compensation for the private cost associated with expanding their balance sheets. This prediction aligns closely with the empirical patterns observed in FX markets during the 2008 financial crisis and the COVID-19 shock, where trading volume remained elevated while the price impact of that volume increased sharply. Chapter 5 identifies this supply-curve steepening empirically by utilizing variation in dealer CDS spreads as a proxy for the severity of debt overhang, following the methodology developed in Andersen et al. (2019) and Burnside and Cerrato (2025b).

This incentive-based interpretation further shows a puzzling feature of existing empirical evidence. Cespa et al. (2022a) and related studies document that FX volume contains predictive information for currency returns, attributing this to asymmetric information on the demand side. However, demand-based explanations alone fail to account for why volume predictability was largely absent before 2008 and emerged only during periods of severe dealer balance-sheet stress, as documented in Chapter 4. Furthermore, they cannot explain why identical quantity pressures generate substantially larger price effects during crises. Chapter 5 provides a supply-side explanation that complements the demand-side view. Volume becomes informative not only because it may reveal private information but also because it interacts with constrained intermediation capacity to generate amplified price responses. This perspective unifies the microstructure evidence from Chapter 3, which documents the state-dependent nature of the volume–volatility relationship, with the intermediary asset pricing framework of Chapter 5, which identifies the source of that state dependence in the incentives of dealer equity holders.

Chapter 3

Volatility, Trading Volume and Order Flow in Foreign Exchange Markets

Abstract:

This study examines the relationship between trading volume and volatility in FX market. It focuses on the roles of trading intensity, directional order flow, and investor heterogeneity. This chapter uses unique FX market data from 12 countries to fill the gap in research on volume and volatility. The results show a clear positive relationship between trading volume and volatility, which weakens at high trading volume. These findings suggest that the volume–volatility link depends on market conditions. Furthermore, this chapter shows that overall order flow helps explain movements in volatility. This effect is especially strong during periods of heavy buying pressure. The study further separates order flow by investor type. The results reveal clear differences across investors. Order flow from individual traders shows a strong link to volatility. In contrast, order flow from institutional investors has weaker effects. These findings highlight the importance of investor differences and trade direction. Market regulation that takes these factors into account helps improve volatility tracking and risk control capabilities, especially when market activity is high. **Keywords:** JEL Financial Crises(G01); Asset Pricing, Trading Volume, Bond Interest Rates(G12); International Financial Markets(G15); Foreign Exchange(F31); Information and Market Efficiency, Event Studies(G14)

3.1 Introduction

Volatility is a central concept in financial economics. It captures market uncertainty and risk. Furthermore, it plays a crucial role in asset pricing, portfolio allocation, and monitoring financial stability. Large empirical research documents a close relationship between volatility and trading activity, particularly in equity and derivatives markets. Early studies consistently find a positive relationship between trading volume and the magnitude of price changes. This suggests that trading activity reflects the arrival of new information into markets (Karpoff (1987); Schwert (1989); Gallant et al. (1992)).

This volume–volatility relationship has become a standard empirical benchmark in financial economics. It is commonly interpreted through the information-based trading models, including the Mixture of Distributions Hypothesis (Clark (1973)) and the Sequential Information Arrival Hypothesis (Copeland (1976)). These models are grounded in theoretical frameworks of adverse selection and information asymmetry. Kyle (1985) demonstrates how informed traders generate price impact through strategic order submission, while Glosten and Milgrom (1985) shows that market makers update prices based on trade direction under asymmetric information. These frameworks collectively propose that trading volume can serve as a proxy for information flow: when information arrives, investors rebalance their portfolios, trading volume increases, and prices adjust accordingly. The volume–volatility relationship has therefore been widely used to assess market efficiency and the informational role of trading activity (Su et al. (2010)).

However, it remains unclear whether this interpretation holds in the foreign exchange (FX) market. Compared with equity markets, the FX market differs markedly in its institutional structure and trading environment. FX trading is decentralized and over-the-counter. It operates continuously across global time zones, and is dominated by heterogeneous participants such as central banks, financial institutions, multinational corporations, and speculative traders. Exchange rate dynamics are primarily driven by macroeconomic information and order flow rather than firm-specific fundamentals (Lyons (2001); Evans and Lyons (2002)). Moreover, aggregate trading volume in FX markets is not directly observable, and empirical studies often rely on proxies such as tick volume or transaction counts. These structural features raise a fundamental question: does trading volume in FX markets truly reflect information arrival, or does it mainly capture liquidity provision and inventory adjustment?

Although this question is very important, existing research on the volume–volatility relationship in FX markets is still very limited. Galati (2000) uses BIS data to document a positive correlation between unexpected trading volume and volatility for emerging market currencies, which is consistent with the Mixture of Distributions Hypothesis. However, the correlation turns negative during episodes of extreme volatility, suggesting that the relationship may be state-dependent. Chuang et al. (2009) explore the causal direction and find evidence of bidirectional Granger causality between volume and volatility. Giot et al. (2010) and Malinova and Park (2010) extend the analysis using higher-frequency data and confirm the positive association. However, they provide limited insight into the underlying mechanisms. More recently, Cespa et al. (2022a) investigate the information content of FX volume using CLS settlement data. They find that volume helps predict next-day currency returns, but only when the volume combines with the return. They suggest that this combination represents information asymmetry and can predict returns. This finding implies that much of aggregate FX volume itself reflects non-informational activity, and that the informational signal embedded in volume is weaker than commonly assumed. These studies share a common limitation: they treat trading volume as homogeneous, without distinguishing between its directional components or the types of market participants generating it.

A parallel literature in FX microstructure emphasises the role of order flow in exchange rate determination. Evans and Lyons (2002) demonstrates that order flow explains a substantial fraction of exchange rate variation, and they argue that it captures the process through which dispersed information is aggregated into prices. Rime et al. (2010) extend this finding across a broader set of currencies. Menkhoff et al. (2016) show that the information content of order flow varies systematically across client types, with financial customers contributing more to price discovery than commercial or retail participants. Ranaldo and Somogyi (2021) provides the most comprehensive evidence to date, using CLS data across 30 currency pairs disaggregated by four participant categories. They find that the price impact of order flow differs markedly across agent types, consistent with asymmetric information theory. However, these studies focus primarily on the level of exchange rates rather than their volatility. The link between order flow and FX volatility has received considerably less attention.

A small number of studies have begun to address this gap. Chan and Fong (2000) show that order imbalance influences the volume–volatility relationship. Daigler and Wiley (1999) and Kartsaklas (2018) document that volatility effects differ across trader categories. In equity markets, recent work highlights the destabilising role of retail investors. Boehmer et al. (2021) documents a significant increase in retail market participation. Eaton et al. (2022) exploit brokerage platform outages and show that reduced retail participation leads to lower volatility and improved liquidity. Baig et al. (2022) further demonstrates that the destabilising effect of retail trading intensifies during periods of crisis. Whether similar dynamics operate in the foreign exchange market remains an open question.

Addressing this question requires going beyond a simple correlation between trading volume and volatility. If trading volume primarily reflects information flow, its relationship with volatility should be stable across market conditions and remain significant after accounting for directional trading. In contrast, if trading volume is largely driven by non-informational activity, its explanatory power should weaken during periods of intense trading, while order flow and trade direction should play a more prominent role. Moreover, if information is processed heterogeneously across market participants, the volatility effects of trading activity should differ across investor types.

The FX market provides a uniquely suitable setting to evaluate these predictions. As the largest and most liquid financial market in the world, FX trading processes vast amounts of information on a continuous basis. According to the 2022 BIS Triennial Survey, average daily FX trading volume exceeded 7.5 trillion US dollars. In recent years, it has increased, partly driven by greater activity in short-maturity derivatives and more inter-dealer trading (Drehmann and Sushko (2022)). High liquidity and narrow bid–ask spreads limit opportunities for market manipulation. This increases the likelihood that observed trading activity reflects genuine information processing. At the same time, the decentralised structure of the FX market implies that order flow (the net directional trading pressure) may provide a more direct measure of information content than aggregate trading volume.

This chapter seeks to fill the gaps identified above. We address four main questions. First, we test whether the volume–volatility relationship is still positive in FX markets. Second, we examine how this relationship varies across trading intensities. Third, we assess whether order flow provides additional explanatory power beyond trading volume, and whether buying and selling pressures have asymmetric effects. Fourth, we investigate whether volatility effects differ across investor types.

The data cover twelve major currencies over the period from 2001 to 2012. This period includes calm market conditions as well as major events such as the global financial crisis. The study examines both realised volatility (proxied by absolute innovation) and implied volatility derived from currency options. This dual approach allows a comparison between actual price movements and market expectations of future uncertainty. The analysis proceeds in four stages: we first test the volume–volatility relationship for each currency, then sort observations into four portfolios by trading volume. After this, we proceeded with a portfolio analysis based on order flow. Finally, we disaggregate order flow by four customer types: asset managers, corporate clients, hedge funds, and private clients.

The results yield several findings. Across most currencies, trading volume is positively related to realised and implied volatility, consistent with evidence from equity markets (Karpoff (1987); Chuang et al. (2009); Giot et al. (2010)). However, portfolio analysis reveals that this relationship is state-dependent: as trading volume increases, the marginal impact of trading volume on volatility weakens significantly. This suggests that most new trading in active markets reflects non-informational activities such as liquidity provision and inventory adjustments. Furthermore, when trading volume increases, institutional activity becomes more dominant, and the average information content of trading volume decreases.

Introducing order flow adds a directional dimension that trading volume cannot capture. Portfolios dominated by selling pressure exhibit negative volatility coefficients, while portfolios dominated by buying pressure exhibit positive volatility coefficients, and the volatility coefficients increase monotonically in the order flow distribution. This asymmetry is consistent with the view that buying pressure is more likely to reflect new information or shifting expectations, whereas selling pressure often represents planned hedging or systematic position reduction (Evans and Lyons (2002); Malinova and Park (2010)).

Disaggregating by trader type reveals that the source of order flow is as important as its direction. Retail order flow generates a volatility impact five to seven times larger than institutional order flow, despite retail investors accounting for only 10 to 20 percent of total volume. Institutional trading is more systematic and predictable, and is absorbed by the market with lower price impact. Corporate hedging flows can even dampen volatility. This heterogeneity is consistent with Menkhoff et al. (2016) and Ranaldo and Somogyi (2021), and helps explain both the declining marginal effect of aggregate volume and the buy–sell asymmetry in order flow.

These findings have significant economic implications. First, they remind us not to blindly use trading volume as an indicator of information arrival in the foreign exchange market, especially during periods of high liquidity. In such times, trading volume may primarily reflect non-informational transactions. Second, they emphasise the central role of targeted order flows in volatility formation, supporting dealer-based information aggregation models (Lyons (2001); Evans and Lyons (2002)). Third, for policymakers and central banks, the findings suggest that monitoring targeted order flows, particularly those from non-institutional markets, may provide more timely signals of market pressure than simply monitoring total trading volume. For corporate finance managers managing foreign exchange risk exposure, understanding the different impacts of institutional and retail order flows on volatility can help develop more effective hedging strategies.

3.2 Data

3.2.1 Data Description

This study examines twelve highly liquid currencies: Euro (EUR), Japanese Yen (JPY), British Pound (GBP), Swiss Franc (CHF), Australian Dollar (AUD), New Zealand Dollar (NZD), Canadian Dollar (CAD), Mexican Peso (MXN), South African Rand (ZAR), Korean Won (KRW), Singapore Dollar (SGD), and Hong Kong Dollar (HKD). The U.S. dollar (USD) is excluded because it is the base currency in all exchange-rate quotes.

Weekly end-user trading volume (Vlm) and order flow (OF) are obtained from a major foreign-exchange dealer and cover more than eleven years. Spot exchange rates for all currencies are collected from WM/Refinitiv (via Datastream). All exchange rates are quoted against the U.S. dollar and expressed as foreign currency units per USD. One-month at-the-money implied volatility (IV) is sourced from Bloomberg and is based on the Black–Scholes framework. Because Bloomberg reports IV in percentage points, IV is divided by 100 before analysis.

The final sample contains 543 weekly observations for each currency for exchange-rate returns, implied volatility, trading volume, and order flow, spanning from the first week of November 2001 to the fourth week of March 2012. This chapter shows the data description in Table 3.1.

3.2.2 Portfolio Description

Adjusted order flow. Because order flow differs in scale across currencies, order flow is standardised to facilitate cross-currency comparisons:

$$y_{i,t} = \frac{x_{i,t}}{std(i_t)} \tag{3.1}$$

where $x_{i,t}$ denote the aggregate order flow (the total value of buy orders, net of sell orders) for currency i in the interval between periods t and t + 1, and $std(x_t)$ is the standard deviation of the order flow of currency i over the full sample.

Exchange-rate returns. Since spot exchange rates are typically nonstationary and differ greatly in level across currencies, the analysis uses log returns:

$$R_{i,t} = log(p_{i,t}) - log(p_{i,t-1}) \tag{3.2}$$

where $R_{i,t}$ is the return rate of exchange price of currency i at time t, and the $p_{i,t}$ is the exchange price of currency i at time t.

Weekly portfolio sorting. At each week t, currencies are sorted into four portfolios based on either trading volume or adjusted order flow. Specifically:

- Volume-sorted portfolios group currencies from lowest volume (V1) to highest volume (V4).

- Order-flow-sorted portfolios group currencies from most negative order flow (net selling pressure) (OF1) to most positive order flow (net buying pressure) (OF4).

Implied volatility and returns are carried along with the currencies in each portfolio so that volatility and trading activity are matched by date.

This chapter shows the portfolio description in Table 3.2 and 3.3.

Customer-type order flow. Order flow disaggregated by customer type—Asset Manager (AM), Hedge Fund (HF), Corporate (CO), and Private Client (PC)—is available only for seven developed currencies (EUR, JPY, GBP, CHF, AUD, NZD, CAD). For this subset, currencies are sorted into three portfolios each week. Because these are major currencies, order flow is not standardised in this subsample.

3.2.3 Descriptive Statistic

Appendix 3C reports descriptive statistics for exchange-rate levels and returns, trading volume, order flow, realised-volatility proxies, implied volatility, and related portfolio ratios.

Figure 3.3 shows the time series plots of the original volume and adjusted order flow datasets by 4 different portfolios. Because the change of these two series is too big, this chapter uses the 4-week rolling windows to replot the time-series plots, which is Figure 3.4. We can see that the volume data was relatively stable before the middle of 2017, and during the second half of 2017, there was a huge change. The volume firstly decreases to the bottom and then bounces back to the top. After this period, the fluctuation of volume has been very big. For the order flow, the figures show that the overall trend in the value of all 4 portfolios increases over time. This tendency means the absolute value of negative order flow decreases, implying that the sell-side volume is decreasing over time. Besides, the value of positive order flow becomes large, implying an increase in the buy-side. It is easy to find that during the second half of 2017, the order flow data shows a booming increase in the middle of 2017, and until 2019, the order flow drops back to the normal value and then increases steadily. This big jump means that during this period, people sold fewer currencies and bought more.

Appendix 3C also presents time-series plots and distributions for key variables to illustrate their evolution and cross-sectional dispersion.

Figure 3.5 and 3.6 shows the time series plots of volatility and implied volatility by 4 different portfolios. Because data of volatility and implied volatility should be matched with volume/order flow at the same date, this chapter separately creates two diagrams by two situations, one portfolio are sorted by order flow (Figure 3.5) and the other one portfolio is sorted by volume (Figure 3.6). We use monthly volatility to replace the weekly volatility to make the plots, which aims to make the diagrams look clearer and can help us more easily observe the characteristics of these two data series. [1] It can be observed that the trend of all portfolios over time is similar between volatility and implied volatility in both 2 situations. At the end of 2018, the change of these two kinds of volatility had an explosive growth, and until the beginning of 2010, it tended to normalise. In addition, the change of these two kinds of volatility is relatively stable. Secondly, diagrams in 3C.2 virtually helps us to see the distribution of our data. We can see that in normal times, people mostly buy or sell currencies at low levels. However, sometimes there also exists some big deal. Furthermore, the larger the volatility data is, the less frequently it appears.

[1] The transformation from weekly volatility into monthly volatility has been attached to appendix 3A.

3.3 Model

3.3.1 Volatility Measures

This section firstly introduce the concept mentioned in this chapter. It will mainly focus on the two different kinds of volatility in our research. We introduce the realised volatility proxy (absolute innovation) and implied volatility and make a comparison of these two different kinds of volatility, which is summarised in Appendix 3B.

Realized-volatility proxy. Following a return-dynamics approach similar in spirit to Schwert (1989), weekly returns are modelled as an autoregression:

$$R_{i,t} = \sum_{j=1}^{n} \beta_j R_{i,t-j} + \epsilon_{it} \tag{3.3}$$

where $R_{i,t}$ is the rate of return of exchange price of currency i at week t. ϵ_{it} is the residual term. L=1,4,8,12 is the selected lag set. The volatility proxy is defined as the absolute innovation:

$$Vol_{i,t} = |\epsilon_{it}| \tag{3.4}$$

Lag selection is based on comparing fit statistics across candidate lag sets; 1,4,8,12 provides consistently strong fit across currencies.

Implied volatility. Implied volatility IV_{it} is the one-month at-the-money implied volatility from Bloomberg (scaled by dividing by 100).

3.3.2 Normalized Volume

To mitigate heteroskedasticity and slow-moving trends in volume, normalized volume is defined as:

$$nv_{i,t} = log(Vlm_{i,t}) - log(\frac{\sum_{s=1}^{N} Vlm_{i,t-s}}{N}) \tag{3.5}$$

where $nv_{i,t}$ is the normalized volume, $Vlm_{i,t}$is the original volume. $N \in \{4, 12\}$. With weekly data, N=4 approximates a monthly window, and N=12 approximates a quarterly window.

3.3.3 Volume/Order Flow and Volatility Regressions

To test whether trading activity predicts volatility while allowing for volatility persistence, the baseline specifications are:

Realized-volatility proxy:

$$Vol_{i,t} = \alpha_i + \sum_{j=1}^{n} \rho_{ij} Vol_{i,t-j} + \beta_i Activity_{i,t} + \eta_{it} \tag{3.6}$$

where $Activity_{i,t}$ is either volume ($Vlm_{i,t}$), normalized volume $nv_{i,t}$, or adjusted order flow $y_{i,t}$.

Implied volatility:

$$IV_{it} = \omega_i + \sum_{j=1}^{n} \lambda_{ij} IV_{i,t-j} + \theta_i Activity_{i,t} + \mu_{it} \tag{3.7}$$

3.4 Preliminary Results

This section begins with how trading volume relates to volatility for individual currencies. Tables3.4 and 3.5 show our baseline regression results for twelve major currency pairs. Each pair involves the U.S. dollar as base currency. Table 3.4 uses raw trading volume as our main explanatory variable. Table 3.5 takes a different approach which uses normalized volume.

When we see the results across all currencies, a clear pattern emerges. Trading volume connects positively with both types of volatility. The connection shows up most strongly for major currencies. EUR, JPY, and CHF all display this pattern clearly. The relationship holds up even after we normalize volume. We do notice something different for less liquid currencies though. Their connection between volume and implied volatility appears weaker. Sometimes it doesn't reach statistical significance at all. This makes sense when we think about how option markets work in these currencies. They have less liquidity. Information may flow differently into option prices (Fleming et al. (1998)). Overall, these findings support a straightforward interpretation. When trading activity picks up, prices fluctuate more. This increased activity also shapes the volatility expectations that get embedded in option prices.

Table 3.4 gives us more specific details. Ten currencies out of twelve show positive coefficients for realized volatility. Nine of these ten reach statistical significance. But the size of these coefficients varies quite a bit. EUR shows a coefficient of 0.10665. At the other end, NZD reaches 2.86580. What drives this variation? Different currencies have different market structures. They attract different types of traders. Liquidity varies across markets (Lyons (2001)). Two currencies stand out as exceptions. GBP and KRW don't reach statistical significance for realized volatility. HKD presents an interesting case too. It shows significance for realized volatility but not for implied volatility.

Table 3.5 shows what happens when we normalized volume. We divide each currency's volume by its own historical average. This normalization doesn't make the positive relationship disappear. In fact, all twelve currencies now show significant positive coefficients for realized volatility. This finding matters because it rules out a simple explanation. We're not just seeing mechanical effects from differences in market size. The relationship reflects something real about how markets work. The normalization also helps clarify the implied volatility picture. Several currencies such as CHF, AUD, and SGD, show sharper results after normalization. This suggests something specific about how markets process information. When trading deviates from its normal level for a particular currency, that deviation may carry special meaning for forward-looking volatility.

Overall, the country-level evidence shows a robust positive link between trading activity and realized volatility across currency markets. This relationship remains strong after mitigating heteroskedasticity and trends in the time series of volume through normalization. Our results are consistent with the relationship of volatility and volume in the stock market(Jones et al. (1994), Karpoff (1987) and recent works (Chuang et al. (2009), Giot et al. (2010), Malinova and Park (2010)). The results for implied volatility indicate that trading activity also shapes forward-looking volatility expectations. Trading volume, whether raw or normalized, measures the intensity of market activity but does not capture trading motives or trade direction. The analysis therefore cannot distinguish between volatility driven by liquidity needs and volatility driven by information-based trading. These limitations motivate the next stage of the analysis. The subsequent sections examine whether the volume–volatility relationship varies across trading-intensity regimes.

3.5 Does the trading volume level influence volatility-volume relationship?

To gain a deeper sense of the relationship between volatility and volume, this chapter further generates 4 portfolios according to the size of volume. This sorting procedure serves two purposes. First, it provides a non-parametric assessment of the robustness of the relationship. Second, it allows for the possibility that the underlying mechanism linking trading activity and volatility differs across market states.

3.5.1 Relationship Statistic

Before doing the empirical test, this section firstly creates the scatter plots for every two variables and tries to visually find the relationship between volatility/implied volatility and volume. Figure 3.1 shows the performance of each kind of volatility based on 4 portfolios that we created before. Comparing two figures of volatility and implied volatility, the characteristics of the relationship between volatility/implied volatility and volume are similar. In the (a) and (b) of Figure 3.1, we can seen that both volatility and implied volatility are nearly linear related with the log of volume. Additionally, from Appendix 3C.3, we find that across portfolios 1-4, as volume increases, the sizes of both volatility and implied volatility show a downward trend overall. Besides, the larger the volume is, the more concentrated the scatters are.

Diagrams(c) of Figure 3.1 make the quantile scatter plots for the entire data to observe the overall trend of the relationship between volatility/ implied volatility and volume. We take volume as the main variable, construct the deciles of it, then calculate the average value of volatility and implied volatility in each decile and draw the scatter plots of them. It can be found that the relationship between the two kinds of volatility and volume is nearly linear, and with the increase in volume, the volatility and implied volatility will increase. However, with the volume increasing, the slope of volatility-volume is smaller and smaller, which indicates that when the volume is larger, the influence on volatility becomes smaller.

From the diagrams here, we can easily find that in the currency markets, the volatility and volume is related. Furthermore, when trading is more intense, the volatility increase more.

3.5.2 Empirical Results

This section shows the empirical test of whether the relationship between volume and volatility will change when the volume increase. This section do the regression on four different 4 portfolios (where V1 include the lowest volume and V4 includes the highest volume) by using the same equation.

Table 3.6 reports a positive relationship between trading volume and the realized volatility proxy in the first three portfolios.[2] The estimated coefficients decline from the lowest to the third portfolio. This positive volume-volatility relationship aligns with the empirical patterns documented by Karpoff (1987), who surveys evidence across multiple asset classes showing that volume and volatility co-move contemporaneously. However, our portfolio evidence reveals that this relationship exhibits regime-dependent variation. This pattern suggests that as trading intensity increases, the information content of trading volume may exhibit diminishing marginal impact. Kyle (1985) demonstrates theoretically that informed traders generate price impact through strategic order submission, and the informativeness of trading depends on the proportion of informed versus uninformed activity. In low-volume environments, incremental trades are more likely to reflect the arrival of private information, consistent with sequential information models (Easley and O'hara (1987); Glosten and Milgrom (1985)). However, as

[2]In order to keep the correctness and rigour, this chapter also does the regression for the relationship between volatility and volume when the rolling average window in equation(3.5) equals 12. Because this chapter used weekly data, when the rolling window equals 12, we can see that as the seasonal average. This chapter shows the results when N= 12 in Appendix 3D.2. We can see that we get the same conclusion.

trading activity intensifies, a larger proportion of trading volume may be attributed to liquidity supply, inventory adjustments, or hedging needs (Lyons (2001)), thereby reducing the marginal sensitivity of volatility to additional trading activity.

Portfolio evidence suggests that increased trading volume leads to a significant increase in volatility; however, as trading volume gradually increases, the marginal effect of this positive impact diminishes, sometimes even becoming statistically insignificant. This pattern aligns with the phenomenon of diminishing marginal information content in trading volume or increased bilateral participation under high trading activity.

In the portfolios with the highest trading volume, the coefficient on trading volume becomes statistically insignificant. This result does not reject the link between trading volume and volatility. Instead, it suggests that the drivers of volatility may change when trading activity becomes extremely high. High trading volume often occurs around major macroeconomic announcements and can also appear during periods when the whole market pays close attention to new information. In these situations, volatility may result more from different interpretations of public information (Harris and Raviv (1993); Kandel and Pearson (1995)) or from imbalances in directional order flow (Menkhoff et al. (2016)) than from additional trades themselves. At the same time, market depth usually increases during high-activity periods. Deeper markets can absorb order flow shocks more efficiently. This mechanism weakens the direct link between current trading volume and volatility.

The results for implied volatility show a related but slightly different pattern. The middle portfolios display significant positive coefficients. These results indicate that higher spot trading activity is associated with higher option-implied volatility. This finding points to information spillovers across markets (Fleming et al. (1998)). In contrast, the lowest-volume portfolio does not show a significant relationship. This outcome suggests that during quiet periods, option-implied volatility responds less to current spot trading activity. Instead, it may reflect broader expectations about future uncertainty. This difference shows that realised volatility and implied volatility process trading information over different time horizons and through different information sets.

Table 3.7 replaces raw trading volume with normalised volume. Most portfolios still show statistical significance. These results reduce the concern that the earlier findings are driven by heteroskedasticity and slow-moving trends. More importantly, the results show that deviations from normal trading levels are systematically related to changes in volatility. Absolute volume levels appear less informative than departures from typical activity.

The implied volatility regression for the lowest portfolio produces another interesting result. Normalised volume enters with a negative coefficient. This sign change suggests that unusually low trading activity may coincide with lower uncertainty or lower perceived information asymmetry (Milgrom and Stokey (1982)). When trading intensity falls far below its historical average, market participants may view the environment as stable. This perception can lead to lower expected volatility. Another possible explanation is that informed traders temporarily step back from the market. In that case, forward-looking volatility measures decline as well. These explanations remain tentative. However, they highlight that the relationship between trading volume and volatility depends on the market state.

Overall, the portfolio analysis shows that the link between trading activity and volatility depends strongly on the trading regime (Ang and Timmermann (2012)). Aggregate trading volume appears more informative in low and moderate activity states. Its explanatory power declines in high-activity periods. In those periods, liquidity-related and inventory-related trades become more important. Directional order flow may then provide a clearer signal of information aggregation (Evans and Lyons (2002)). These findings suggest that trading volume does not serve as a single, stable proxy for information arrival in FX markets. Instead, its meaning changes with market conditions.

3.6 Order Imbalance and Volatility

While volume captures the intensity of market activity, it does not distinguish between buyer-initiated and seller-initiated trades. Research in foreign exchange microstructure suggests that the directional component of trading order flow contains more direct information about price dynamics and volatility than aggregate volume (Evans and Lyons (2002); Rime et al. (2010)). Order flow measures net buying pressure and reflects how dispersed information is aggregated through signed transactions(Hasbrouck (1991)). We therefore extend the portfolio analysis by sorting on order flow rather than trading volume.

Figure 3.2 displays the relationship between volatility/implied volatility and order flow. Diagrams (a) and (b) show that nearly all portfolios exhibit a linear relationship between volatility and order flow. When order flow is close to zero, the scatters become more clustered, and the slopes steepen, implying that volatility is more sensitive to marginal changes in order flow when buy and sell pressures are nearly balanced. In diagram (c), the relationship takes a concave shape: volatility relates negatively to order flow under selling pressure but positively under buying pressure, with values near zero at balanced order flow. This suggests that markets remain stable when buy and sell pressures offset each other, but become more volatile when either side dominates.

Table 3.8 presents regression results across four portfolios, where Portfolio 1 represents the strongest net selling pressure and Portfolio 4 the strongest net buying pressure. The estimated coefficients increase monotonically from negative to positive, indicating that the direction of order flow plays a central role in shaping volatility dynamics.

In Portfolio 1, the coefficient for realised volatility is significantly negative (-1.12158, p=0.05), and the implied volatility coefficient is also negative (-3.12501, p=0.09). When order flow becomes heavily imbalanced toward selling, it may indicate substantial agreement among participants regarding price direction, thereby reducing disagreement-driven volatility. Chordia et al. (2002) document that persistent order imbalances facilitate price discovery by revealing the direction of informed trading, which reduces price uncertainty. Additionally, liquidity providers can manage inventories more efficiently under predictable one-sided flow (Stoll (1978)), absorbing orders with lower price impact.

Portfolio 2 exhibits no significant relationship between order flow and either volatility measure. Under relatively balanced conditions, incremental changes in net direction may reflect noise rather than systematic information. In Portfolio 3, buying pressure begins to dominate. Both realised volatility (2.32461, p=0.05) and implied volatility (6.80766, p=0.10) enter with positive and significant coefficients. Portfolio 4, with the strongest buying pressure, maintains this positive relationship, with realised volatility reaching 1.86541 ($p<0.01$).

The contrast between Portfolios 1 and 4 is particularly instructive. Evidence from equity markets suggests that buy-side and sell-side imbalances carry different information content. Chordia et al. (2002) and Hasbrouck and Saar (2009) document that buying pressure often accompanies new information or positive sentiment shifts. This creates uncertainty about appropriate price levels, leading to higher volatility. Selling pressure more commonly originates from routine portfolio adjustments or planned inventory reductions, generating less informational surprise.

The concept of "order flow toxicity" (Easley et al. (2012)) helps explain this asymmetry. In Portfolio 1, if selling pressure mainly comes from uninformed traders or hedgers, the adverse selection risk for liquidity providers is low. This allows them to accommodate orders with modest price adjustments. In Portfolios 3 and 4, buying-side imbalances may reflect informed trading. This prompts liquidity providers to widen spreads and adjust prices more aggressively as a defence against adverse selection (Glosten and Milgrom (1985)), which amplifies realised volatility. The weaker response of implied volatility in Portfolio 4 suggests that the volatility spike from buying pressure is a temporary price pressure rather than a permanent shift in market conditions (Hendershott and Menkveld (2014)).

These findings carry significant implications. Unlike trading volume, which treats all transactions the same, order imbalance includes both the quantity and the primary direction of trading activity. This directional content is particularly valuable in the decentralised foreign exchange market, where information is distributed among heterogeneous participants (King et al. (2013)). The positive relationship between order flow and volatility, combined with the pronounced buy–sell asymmetry, demonstrates that signed order flow captures microstructure dynamics that volume alone cannot reveal.

Our results align with dealer-based models of exchange rate determination (Evans and Lyons (2002); Lyons (2001)), which emphasise that currency markets process information primarily through the direction of order flow.

3.7 Volatility and customer types (AM/HF/CO/PC)

Our previous analysis demonstrates that order flow imbalances systematically affect volatility. However, the foreign exchange market comprises diverse participants with different information endowments, trading motives, and operational constraints. We therefore disaggregate order flow by four customer categories: asset managers, corporate clients, hedge funds, and private clients. Table 3.9 presents regression results for each type across three order flow portfolios.

The results reveal significant differences across client types. Institutional investors (asset management companies and hedge funds) have relatively low volatility coefficients. For asset managers, the coefficients in Portfolios 1 and 3 range from -3.50595 to 2.54250 (both $p < 0.01$). Hedge funds show similar magnitudes, with realised volatility in Portfolio 3 reaching 2.35528 ($p = 0.04$). A notable distinction is that hedge funds exhibit a divergence between realised and implied volatility in Portfolio 3 (2.35528 vs -4.42696). This implies the aggressive strategies generate short-term realised volatility, but the information revealed through their trading appears to reduce forward-looking uncertainty (Pojarliev and Levich (2010)).

Corporate clients display a distinct pattern. The realised volatility coefficients in Portfolios 2 and 3 are both significantly negative (-11.19615 and -14.71994, respectively). This reflects their hedging-oriented motive: corporate clients manage currency risk exposures arising from international operations rather than engaging in speculative activity (Allayannis and Ofek (2001)). Their coordinated hedging flows stabilise rather than amplify volatility.

Private clients exert a disproportionately large influence. Portfolio 2 has a realised volatility coefficient of 17.34210(p=0.02) and an implied volatility coefficient of 48.02740($p < 0.01$). Portfolio 3 maintains a strong effect at 13.92305($p < 0.01$). These coefficients are five to seven times larger than those of institutional investors. This pattern is consistent with evidence that retail investors trade in a more sentiment-driven and less systematic manner than institutional participants (Barber and Odean (2000); Kumar and Lee (2006)).

Several mechanisms explain this outsized impact. First, retail order flow is noisier and harder for market makers to interpret. When liquidity providers cannot distinguish informed from uninformed flow, they widen spreads and adjust prices more aggressively (Kyle (1985)), amplifying volatility. Second, retail trading often reflects temporary reactions to news or sentiment rather than fundamental portfolio management (De Long et al. (1990)). This produces demand patterns that appear decoupled from economic fundamentals. Third, retail order flows may represent genuine final demand rather than intermediary rebalancing, reflecting actual shifts in market sentiment that require price adjustment (Menkhoff et al. (2016); Chague et al. (2020)). Recent work corroborates these dynamics: Boehmer et al. (2021) find that retail participation systematically exacerbates volatility, particularly during periods of market stress, while Eaton et al. (2022) show that retail flows exhibit stronger momentum and reversal patterns, amplifying volatility through feedback loops.

This client-level heterogeneity helps clarify two earlier findings. First, it explains the diminishing marginal effect of total trading volume on volatility. Institutional investors dominate overall volume in the foreign exchange market (King et al. (2013)), but their trading primarily involves liquidity provision and systematic rebalancing rather than information-driven directional activity (Ranaldo and Somogyi (2021)). As total trading volume increases and the proportion of institutional participants rises further, the overall information contained in trading volume decreases. Meanwhile, individual clients account for only 10% to 20% of total trading volume, but their significant impact on volatility means that at high trading volume levels, the information contained in trading volume is diluted.

Second, client heterogeneity explains the asymmetric relationship between order flow and volatility documented in Table 3.8. If retail clients are more concentrated in certain order flow patterns (e.g., retail buying may dominate during periods of market optimism) while institutional clients' order flows are more evenly distributed, this compositional difference creates the observed asymmetry. Similarly, if corporate hedging flows are systematically biased towards the sell side (e.g., hedging expected overseas returns), this can result in negative volatility coefficients for extreme sell portfolios. Breedon et al. (2016) supports this interpretation, finding that the composition of client order flows in foreign exchange markets shifts systematically with market conditions.

In summary, order flow functions as a multidimensional signal: interpreting its volatility implications requires understanding not only its direction and magnitude but also its source. These findings are consistent with microstructure models that emphasise trader heterogeneity as a fundamental determinant of volatility (Bloomfield et al. (2009); Biais et al. (2015)) and extend recent empirical work on client segmentation effects in foreign exchange markets (Cespa and Vives (2015)).

3.8 Robustness Tests (Financial Crisis + SUR)

3.8.1 Crisis Control

The datasets we used in this chapter are from 2001 to 2012, which includes the financial crisis in 2008. In order to control the effect of the financial crisis on our model, A crisis dummy for December 2007–June 2009 is included both in the return model used to construct the volatility proxy and in the volatility regressions.

$$R_{i,t} = \sum_{j=1}^{n} \beta_j R_{i,t-j} + \upsilon d_{i,t} + \tau_{it} \tag{3.8}$$

Equation(3.8) shows the realized volatility proxy model adding the dummy variable. We decide the duration from December of 2007 to June of 2009 as the financial crisis period according to the business cycle from NBER, and let $d_{i,t}$ as the dummy variable which equals 1 during the financial crisis, otherwise equals 0. τ_{it} is the residual term which is used to express volatility. In this chapter, we call the volatility calculated by equation (3.8) dummy volatility.

Realized-volatility proxy:

$$Vol_{i,t} = \alpha_i + \sum_{j=1}^{n} \rho_{ij} Vol_{i,t-j} + \beta_i Activity_{i,t} + \varphi D_{i,t} + \eta_{it} \tag{3.9}$$

where $Activity_{i,t}$ is either volume ($Vlm_{i,t}$), normalized volume $nv_{i,t}$, or adjusted order flow $y_{i,t}$.

Implied volatility:

$$IV_{it} = \omega_i + \sum_{j=1}^{n} \lambda_{ij} IV_{i,t-j} + \theta_i Activity_{i,t} + \varphi D_{i,t} + \mu_{it} \tag{3.10}$$

where $D_{i,t}$ is the dummy variable which equals to 1 during the financial crisis period, otherwise equals to 0. This chapter does the regression with dummy variables by using the portfolios set up before(V1-V4 and OF1-OF4), so the i in all these five equations indicates each portfolio.

According to the new volatility calculated by equation (3.8), this chapter firstly try to check whether financial crisis variable make new volatility have difference from the original one. In order to this, before doing the regression, we firstly re-draw the relationship plots of dummy volatility and volume/ order flow. And we show the results in Appendix 3E.1 Figure 3.18 shows the relationship between dummy volatility and volume. It can be seen that after controlling the financial crisis, the number of noisy point is less than before. Figure 3.18 (b) shows the overall trend between dummy volatility and volume. We can find that on the whole, the quantile plot is similar to the old one, which shows the positive relationship between volatility and volume. Figure 3.19 contains the relationship plots between dummy volatility and order flow. The figure still has the low volatility around the middle of the order flow and achieves high at the first and last quantiles, which is the same as without a financial crisis.

After the visual relationship analysis, this chapter further performs empirical tests, and the regression results are shown in Tables 3.10-3.11. In Table 3.10, it can be observed that portfolio 1-3 of volatility and portfolio 2 and 3 of implied volatility get significant results. We can find that the characteristics we observed in Tables 3.10 is similar to former results. This indicates that the financial crisis has an effect on our model; however, it does not impact our results and our overall findings. The main qualitative conclusions remain: volume retains a positive association with volatility, and marginal effects decline across volume-sorted portfolios. [3]Table 3.19 shows the relationship results between volatility and order flow. We find that both portfolio1's volatility and implied volatility remain negative, supporting our earlier conclusion that sell-side order flow negatively affects volatility. Furthermore, the portfolio 2-4 got the positive but decreasing coefficient results, which is also the same as the former conclusion. This means the financial crisis have effect on our model, however, it does not affect the conclusion we got before. Besides, the original model have the better ability to measure this relationship.

[3]In order to keep results correct, this chapter also shows the log volume results in Figure 3.24, which has been reported in the appendix, and we get the same results.

3.8.2 Cross-portfolio Dependence (SUR)

This chapter divides the full sample into four portfolios and estimates the regressions described above in order to examine how volatility varies with trading volume and the directional components of order flow. However, partitioning the sample into multiple sub-samples may potentially affect the estimation results. To assess whether the findings are sensitive to such sample segmentation, we further consider an alternative approach that accounts for the dependence across portfolios. Because portfolio regressions may share common shocks, the portfolio equations are also estimated jointly using a Seemingly Unrelated Regression (SUR) system.

The SUR approach enables us to combine the four portfolio equations into a system and to test whether the portfolios are linked through common unexpected information captured in the residuals. Moreover, this framework allows us to examine whether the main results remain consistent once cross-portfolio dependence is taken into account.

The SUR regression results are reported in Tables 3.12 and 3.13. The chi-square statistics for each equation in both tables are large, and the corresponding p-values are close to zero, indicating strong statistical significance. System-level tests indicate trading activity is jointly significant, supporting the baseline findings after accounting for cross-equation correlation.

3.9 Additional Analysis - Theory Model Analysis

In this section, this chapter undertakes the additional theory to analyse the results proposed before. We try to use the microstructure theory mentioned in The Microstructure Approach to Exchange Rates by Lyons (2001) to explain the phenomenon presented. We first simply introduce the models and then connect them with our research.

According to the theory in The Microstructure Approach to Exchange Rates, there are four distinct models, which are: 1. The rational expectations auction model, 2. Kyle auction model, 3. Sequential-trade model and 4. Simultaneous-trade model. We can summarise them into 2 groups: the models for auction markets and the models for dealer markets. The first two models are set up based on the auction markets where the price is jointly determined by the highest price from the buyer and the lowest price from the seller. This market is a common platform for buyers and sellers to enter competitive offers and bid prices, and the trading price is confirmed when the matching bid and offer come together. The third and the fourth models are set up in the dealer markets where the dealers buy and sell securities uses their own accounts. In this market, the dealer plays the role of market maker, and they quote the bid and offer prices. When investors can accept the prices, they can do the transaction electronically. We can simply summarise that the price in the auction market is order-driven and in the dealer market is quote-driven. considers For perspective on the rational expectations auction model, we assume there are two players in the market, one is informed, and the other is uninformed. Both of these two players are risk-averse and are perfect competitors. This model consider the timing of trading at three points, t_0, t_1, and t_2. The value of the asset at the end of the period (t_2) payoff is V. Before the V is paid, trade occur at t_1 with price equal to P. And before the trade price is determined, the informed trader receives private information symbolised as V at t_0. Furthermore, each trader receives a random endowment, and the sum of their endowments is marked as X also at t_0. This model believes the price P equals the net of the signal S and asset supply X, and the signal S is impacted by the payoff V and the external noise. The rational expectations auction model assumes an implicit auctioneer, and the Kyle model builds on this framework but introduces an explicit auctioneer. In the rational expectations model, prices are directly affected by information. In the Kyle model, information progresses in two stages. First, non-market makers learn fundamentals from direct sources and trade, generating order flow. Second, market makers infer information from the order flow and adjust prices. Unlike the three time points in the rational expectations model, the Kyle model divides time into four points. This model think before the price P is determined and after the signal S has been observed by the informed investors, both informed investors and uninformed investors make the order flow marked as D^I and D^U. What is more, the price P equals the sum of D^I and D^U, which is shown in the equation below.

$$P = \lambda(D^I + D^U) \tag{3.11}$$

and a trading rule for the D^I equals to

$$D^I = \beta V \tag{3.12}$$

where parameter λ and β take the following form

$$\lambda = \frac{1}{2}(\sigma_V^2/\sigma_U^2)^{1/2} \tag{3.13}$$

$$\beta = (\sigma_U^2/\sigma_V^2)^{1/2} \tag{3.14}$$

According to the Kyle model, we can see that the price is positively related to the size of order flow, which is positively related to the volume of trading, especially trading by uninformed investors. When the trading volume from uninformed investors increase, the variance of uninformed trading volume increase and then the β will be bigger. When both D^I and D^U increase, the P will also express the growing trend. What is more, when the variance of uninformed trading increases, the size of λ decreases. This means when volume increases, the price change, which can be seen as volatility, will also increase; however, this growth will marginally decrease as the volume becomes bigger and bigger.

From the perspective of the sequential-trade model, it has several characteristics similar to those of the Kyle model. In both these two models, the dealer is risk-neutral and includes a single optimising dealer whose price is affected by the private information. However, different from the Kyle model, the sequential-trade model is set up in the dealer market. In this model, there is only one single dealer, and the single trade can be divided into 4 steps, which are trader selects, dealer quotes, trader acts, and dealer updates. This timeline is only rational for single-dealer trading; however, for the real market, there are multiple dealers at one time. For this reason, the simultaneous-trade model has been proposed. Different from the sequential-trade model, this model also includes the interdealer trading, so this model sets up a two-period game with N dealers. In the first period, the first event is still the information signal S and S_i, which are common information for all dealers and the private signal received by dealer$i$. After dealers receive the signal, dealer i quotes in period one as P_{i1}. And then each dealer receive orders from their own customers symbolized as C_i. Jointly considering the C_i and the desired position of dealer i (D_i), dealer i get the order to other dealers marked as T_i. Finally, the net interdealer order flow equals to X. In the second period, dealer i quotes at P_{i2}, which is determined by the order flow X from period one, and then the interdealer trading in period two occurs as T_{i2}. Finally, we get the payoff value V. In the simultaneous-trade model, we can summarise the determination of each price as following:

Quoting P_{i1}: C_i, S_i, S

Trading T_{i1}: $C_i, S_i, S, P_{11}, ..., P_{N1}$

Quoting P_{i2}: $C_i, S_i, S, P_{11}, ..., P_{N1}, T_{i1}, X$

Trading T_{i2}: $C_i, S_i, S, P_{11}, ..., P_{N1}, T_{i1}, X, P_{12}, ..., P_{N2}$

It can be seen that the order flow (volume) from customers can affect the first period price which can further impact the change of price that is the volatility of price. Furthermore, the interdealer order flow and the customer order flow can jointly impact the price in period two. This can also be proved by our results in Chapter 3.5-3.7.

3.10 Conclusion

This study investigates how trading volume relates to volatility in the foreign exchange market. By progressively moving from aggregate volume to signed order flow and then to client-disaggregated order flow, we get three main conclusions.

First, the volume–volatility relationship is state-dependent. Most major currency pairs exhibit a positive correlation between trading volume and both realised and implied volatility. Furthermore, portfolio-level analysis reveals that the marginal impact of volume on volatility diminishes as activity levels increase. This pattern is consistent with the view that trades during calmer periods are more likely to carry genuine information (Easley and O'hara (1987)). In high-volume environments, routine liquidity provision and mechanical rebalancing are increasingly dominant, diluting the average information content of volume.

Second, the direction of trading activity also has an important impact. Sorting by order flow rather than volume uncovers a systematic asymmetry. Portfolios with strong selling pressure exhibit negative volatility coefficients, while those with strong buying pressure exhibit positive coefficients. The volatility coefficient increases monotonically between the two. Selling pressure typically reflects planned hedging or position reductions and tends to stabilise prices. Buying pressure, on the other hand, is more likely to be accompanied by new information or changes in expectations, thereby exacerbating price uncertainty. (Evans and Lyons (2002)). This directional dimension is absent from volume measures.

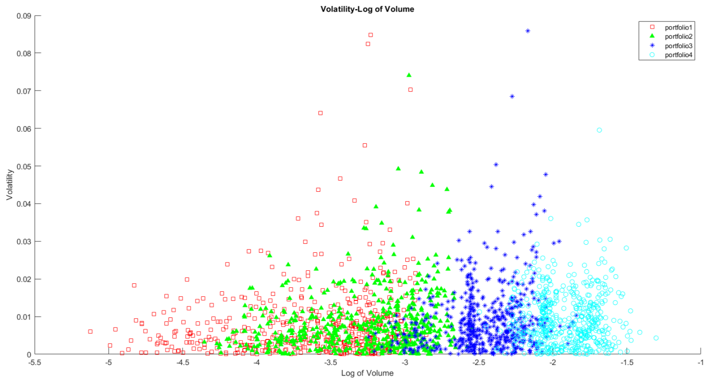
Third, trader identity is a key determinant of how order flow affects volatility. Although retail order flows account for only 10% to 20% of total transaction volume, their impact on volatility is five to seven times that of institutional order flows. Retail trading mixes signal with noise and is more sentiment-driven (Barber and Odean (2000)), forcing market makers to widen spreads under information asymmetry (Kyle (1985)). Institutional order flows have a smaller impact on prices because they are more systematic and predictable. Furthermore, corporate hedging flows can even dampen volatility. This heterogeneity aligns with the views expressed in Menkhoff et al. (2016) and helps explain the diminishing marginal effect of total trading volume and the asymmetry between buy and sell orders. As total trading volume increases, the share of institutional trading grows, thereby reducing the signal implied by trading volume. Simultaneously, retail clients may be concentrated in a buy-side-dominated trading environment, which increases the observed asymmetry.

These findings contribute to the literature in two ways. Theoretically, they challenge models that treat trading volume as a simple proxy for information arrival. Our results demonstrate that volume is a context-dependent signal whose interpretation requires knowledge of both order flow direction and trader composition. This multilayered perspective extends dealer-based models of exchange rate determination (Lyons (2001); King et al. (2013)) by providing empirical evidence on the distinct roles played by different market participants. Practically, our results suggest that volatility forecasting models can be improved by incorporating regime-dependent volume effects, order flow, and shifts in retail participation. For instance, rising retail activity during major political events may signal elevated future volatility even when aggregate volume remains stable.

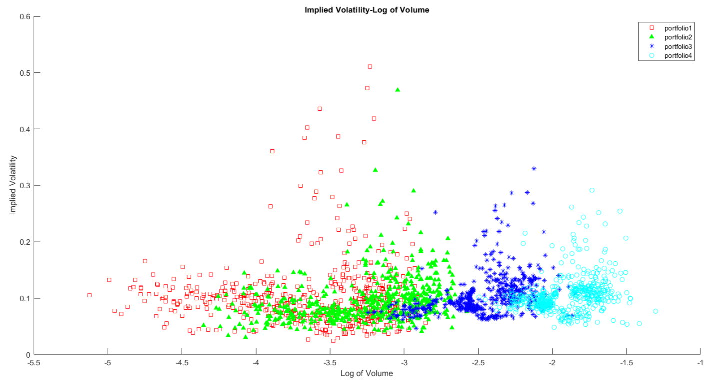
Several limitations point to directions for future research. Our analysis focuses on major currency pairs. Whether similar patterns hold for emerging market currencies or during crisis episodes remains to be tested. More high-frequency data will help clarify the relative contributions of liquidity-driven and information-driven trading to the diminishing marginal effect of trading volume. Finally, examining whether retail investors concentrate their activity in specific market phases and whether this concentration exacerbates the asymmetry between buying and selling will deepen our understanding of the microstructural channels through which trading activity affects volatility.

Figure 3.1: Volume Relationship

(a) Volatility-Log(Volume)



(b) Implied Volatility-Log(Volume)



(c) Quantile Plots of Volatility/Implied Volatility-Volume

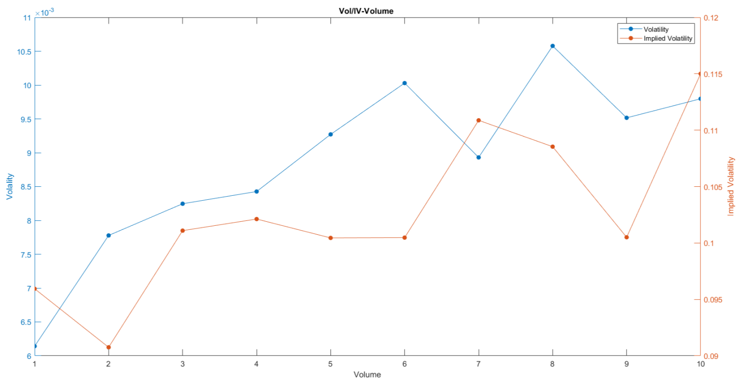
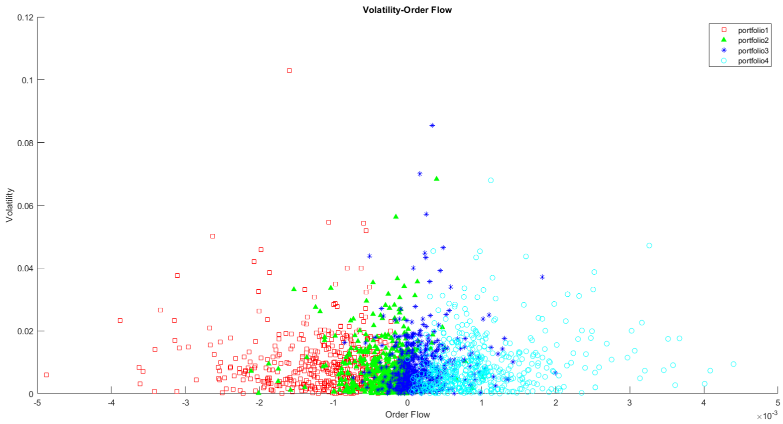
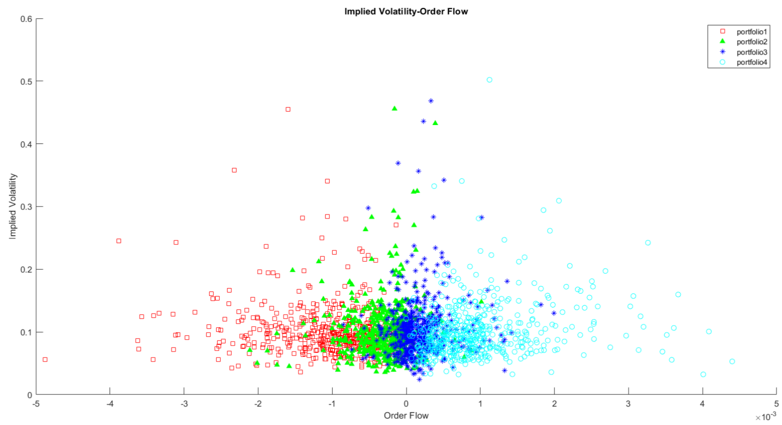


Figure 3.2: Order Flow Relationship

(a) Volatility-Order Flow



(b) Implied Volatility-Order Flow



(c) Quantile Plots of Volatility/Implied Volatility-Order Flow

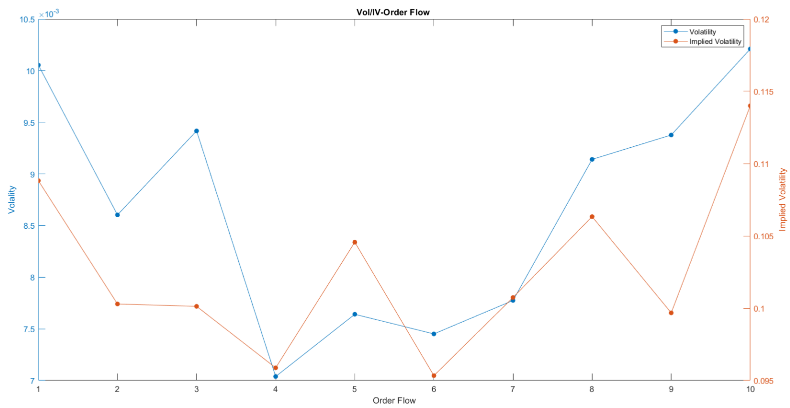


Figure 3.1 Figure 3.2 shows the scatters of relationship between volatility/implied volatility and volume/order flow. The implied volatility has been divided by 100, and the volume and order flow have been divided by 1000.

Table 3.1: Exchange Price and Exchange Price Return Rate of Each Currency

Exchange Price and Exchange Price Return Rate								
Panel A: Exchange Price								
Variables	N	Mean	S.D.	Min	0.25	Median	0.75	Max
EUR	543	0.8	0.12	0.63	0.73	0.77	0.83	1.16
JPY	543	105.49	14.92	75.76	92.05	108.62	117.78	134.83
GBP	543	0.59	0.06	0.48	0.54	0.60	0.64	0.73
CHF	543	1.2	0.19	0.76	1.06	1.21	1.29	1.72
AUD	543	1.31	0.26	0.91	1.11	1.30	1.43	1.98
NZD	543	1.55	0.29	1.14	1.35	1.45	1.65	2.44
CAD	543	1.19	0.19	0.94	1.03	1.16	1.31	1.61
MXN	543	11.42	1.22	9.01	10.71	11.06	12.37	15.28
ZAR	543	7.65	1.37	5.63	6.75	7.30	8.00	12.37
KRW	543	1117.05	128.55	906.80	1009.50	1134.90	1194.65	1550.45
SGD	543	1.55	0.18	1.20	1.40	1.54	1.70	1.85
HKD	543	7.78	0.02	7.71	7.76	7.78	7.80	7.83
Panel B: Exchange price Return Rate (Logarithmic Returns in %)								
Variables	N	Mean	S.D.	Min	0.25	Median	0.75	Max
EUR	542	0	0.01	-0.05	-0.01	0.00	0.01	0.06
JPY	542	0	0.01	-0.08	-0.01	0.00	0.01	0.05
GBP	542	0	0.01	-0.05	-0.01	0.00	0.01	0.09
CHF	542	0	0.02	-0.06	-0.01	0.00	0.01	0.12
AUD	542	0	0.02	-0.07	-0.01	0.00	0.01	0.18
NZD	542	0	0.02	-0.07	-0.01	0.00	0.01	0.12
CAD	542	0	0.01	-0.05	-0.01	0.00	0.01	0.09
MXN	542	0	0.02	-0.06	-0.01	0.00	0.01	0.16
ZAR	542	0	0.03	-0.11	-0.02	0.00	0.01	0.11
KRW	542	0	0.02	-0.10	-0.01	0.00	0.01	0.07
SGD	542	0	0.01	-0.03	0.00	0.00	0.00	0.04
HKD	542	0	0.00	-0.01	0.00	0.00	0.00	0

Table 3.1 shows the descriptive statistic of exchange price and the rate of exchange price return of each currency.

Table 3.2: Volume and Volatility/Implied Volatility Portfolios sorted by Volume

Volume and Volatility/Implied Volatility Portfolios								
Panel A: Volume								
Variables	N	Mean	S.D.	Min	0.25	Median	0.75	Max
Portfolio1	530	0.37	0.3	0.01	0.12	0.32	0.58	1.4
Portfolio2	530	0.75	0.55	0.04	0.28	0.66	1.12	2.86
Portfolio3	530	4.01	2.18	0.57	2.66	3.48	5.33	14.42
Portfolio4	530	13.53	6.33	3.2	8.63	11.98	17.58	49.83
Panel B: Volatility % (sorted by volume)								
Variables	N	Mean	S.D.	Min	0.25	Median	0.75	Max
Portfolio1	530	0.82	0.97	0	0.25	0.55	1.05	8.48
Portfolio2	530	0.84	0.82	0	0.3	0.62	1.1	7.4
Portfolio3	530	0.94	0.9	0.01	0.34	0.72	1.26	8.59
Portfolio4	530	0.94	0.71	0	0.42	0.81	1.36	5.95
Panel C: Implied Volatility % (sorted by volume)								
Variables	N	Mean	S.D.	Min	0.25	Median	0.75	Max
Portfolio1	530	10.41	6.13	2.45	6.92	9.25	11.9	51.08
Portfolio2	530	9.61	4.14	3.05	7.12	8.66	10.96	46.88
Portfolio3	530	10.51	3.65	4.67	8.24	9.72	11.65	32.98
Portfolio4	530	10.5	3.18	4.83	8.74	9.98	11.37	29.14
Panel D: Ratio of IV/Vol (sorted by volume)								
Variables	N	Mean	S.D.	Min	0.25	Median	0.75	Max
Portfolio1	530	121.39	1101.92	3.35	9.08	15.58	36.91	23707.19
Portfolio2	530	99.85	776.22	3.13	8.12	13.91	2.66E+01	12507.71
Portfolio3	530	39.86	124.67	2.76	8.18	13.77	29.18	1564.77
Portfolio4	530	63.94	376.55	2.53	7.56	12.34	24.39	5788.46

Table 3.2 shows the descriptive statistic of volume and volatility/implied volatility sorted by volume. The Panel A shows description of original volume data which is not divided by 1000. Panel B shows the description of Volatility % and the Implied Volatility % which instead the original Volatility and Implied Volatility. The portfolios in Table 3.2 are sorted according to volume.

Table 3.3: Order Flow and Volatility/Implied Volatility Portfolios sorted by Order Flow

Order Flow and Volatility/Implied Volatility Portfolios								
Panel A: Adjusted Order Flow								
Variables	N	Mean	S.D.	Min	0.25	Median	0.75	Max
Portfolio1	530	-1.09	0.71	-4.87	-1.41	-0.93	-0.59	-0.06
Portfolio2	530	-0.3	0.35	-2.11	-0.45	-0.24	-0.07	1.01
Portfolio3	530	0.17	0.32	-0.85	0	0.12	0.29	1.99
Portfolio4	530	0.96	0.69	0	0.5	0.82	1.17	4.4
Panel B: Volatility % (sorted by order flow)								
Variables	N	Mean	S.D.	Min	0.25	Median	0.75	Max
Portfolio1	530	0.94	0.92	0	0.36	0.72	1.28	10.29
Portfolio2	530	0.78	0.77	0	0.25	0.58	1.07	6.84
Portfolio3	530	0.85	0.87	0	0.31	0.64	1.16	8.54
Portfolio4	530	0.9	0.84	0	0.31	0.69	1.19	6.8
Panel C: Implied Volatility % (sorted by order flow)								
Variables	N	Mean	S.D.	Min	0.25	Median	0.75	Max
Portfolio1	530	10.29	4.31	3.59	7.88	9.39	11.51	45.5
Portfolio2	530	10.2	4.61	3.57	7.4	9.41	11.84	45.57
Portfolio3	530	10.35	4.79	2.45	7.47	9.68	11.68	46.84
Portfolio4	530	10.19	4.55	3.22	7.3	9.33	11.68	50.21
Panel D: Ratio of IV/Vol (sorted by order flow)								
Variables	N	Mean	S.D.	Min	0.25	Median	0.75	Max
Portfolio1	530	63.74	462.34	2.92	7.8	13.3	27.62	9720.2
Portfolio2	530	520.35	9890.07	3.21	8.9	15.64	39.44	2.30E+05
Portfolio3	530	89.99	734.84	2.71	8.64	14.53	29.7	13328.03
Portfolio4	530	64.44	537.52	2.97	8.09	13.23	27.74	11792.2

Table 3.3 shows the descriptive statistics of order flow and volatility/implied volatility sorted by it. Panel A shows a description of the original adjusted order flow data, which is not divided by 1000. Panel B shows the description of Volatility % and the Implied Volatility % portfolios, which are instead of the original Volatility and Implied Volatility. The portfolios in Table 3.3 are sorted according to adjusted order flow.

Table 3.4: Results of Volatility/Implied Volatility and Volume–for different currencies

Volume					
Volatility			Implied Volatility		
Currency	Coefficient	p-value	Currency	Coefficient	p-value
EUR	0.10665*	0.00	EUR	0.09073*	0.02
JPY	0.34363*	0.00	JPY	0.44974*	0.01
GBP	0.11900	0.14	GBP	0.15174*	0.07
CHF	0.35153*	0.01	CHF	0.29773*	0.04
AUD	0.85858*	0.00	AUD	0.91510*	0.00
NZD	2.86580*	0.01	NZD	2.80355*	0.02
CAD	1.08706*	0.00	CAD	0.48735*	0.05
MXN	3.50652*	0.01	MXN	3.61476	0.31
ZAR	3.12417*	0.06	ZAR	3.38183	0.13
KRW	0.91428	0.16	KRW	0.93632	0.52
SGD	2.40089*	0.00	SGD	2.88053*	0.00
HKD	0.16432*	0.00	HKD	0.24051	0.24

* indicates statistical significance at 10 % level

Table 3.4 shows the original volume and volatility relationship for different currencies. In this table, this chapter performs a time series regression using the equation below and shows the results of β_i and θ_i.

Realised-volatility proxy:

$$Vol_{i,t} = \alpha_i + \sum_{j=1}^{n} \rho_{ij} Vol_{i,t-j} + \beta_i Activity_{i,t} + \eta_{it} \tag{3.15}$$

Implied volatility:

$$IV_{it} = \omega_i + \sum_{j=1}^{n} \lambda_{ij} IV_{i,t-j} + \theta_i Activity_{i,t} + \mu_{it} \tag{3.16}$$

where $Vol_{i,t}$ is realized volatility and IV_{it} is implied volatility. $Activity_{i,t}$ is volume ($Vlm_{i,t}$) in this table.

Table 3.5: Results of Volatility/Implied Volatility and Normalized Volume–for different currencies

Normalized Volume N=4					
Volatility			Implied Volatility		
Currency	Coefficient	p-value	Currency	Coefficient	p-value
EUR	0.01877*	0.00	EUR	-0.00052	0.92
JPY	0.00666*	0.09	JPY	0.01148*	0.04
GBP	0.01027*	0.01	GBP	0.00656*	0.10
CHF	0.01050*	0.03	CHF	0.01700*	0.00
AUD	0.01135*	0.05	AUD	0.01700*	0.00
NZD	0.01937*	0.00	NZD	0.00998*	0.06
CAD	0.01203*	0.00	CAD	0.00016	0.96
MXN	0.00679*	0.01	MXN	0.00362	0.61
ZAR	0.01598*	0.00	ZAR	0.00806	0.12
KRW	0.00430*	0.01	KRW	0.00356	0.35
SGD	0.00329*	0.00	SGD	0.00283*	0.06
HKD	0.00027*	0.07	HKD	0.00051	0.39

* indicates statistical significance at 10 % level

Table 3.5 shows the normalized volume and volatility relationship for different currencies. In this table, the chapter performs a time-series regression using the equation below and reports the results for β_i and θ_i.

Realised-volatility proxy:

$$Vol_{i,t} = \alpha_i + \sum_{j=1}^{n} \rho_{ij} Vol_{i,t-j} + \beta_i Activity_{i,t} + \eta_{it} \tag{3.17}$$

Implied volatility:

$$IV_{it} = \omega_i + \sum_{j=1}^{n} \lambda_{ij} IV_{i,t-j} + \theta_i Activity_{i,t} + \mu_{it} \tag{3.18}$$

where $Vol_{i,t}$ is realized volatility and IV_{it} is implied volatility. $Activity_{i,t}$ is normalized volume $nv_{i,t}$.

Table 3.6: Results of Volatility/Implied Volatility-Volume– for different portfolios

Volume					
Volatility			Implied Volatility		
Portfolio	Coefficient	p-value	Portfolio	Coefficient	p-value
1	3.49945*	0.01	1	1.78507	0.71
2	2.00071*	0.00	2	6.05482*	0.02
3	0.61965*	0.00	3	0.73744*	0.00
4	0.02567	0.61	4	0.13969*	0.08

* indicates statistical significance at 10 % level

Table 3.7: Results of Volatility/Implied Volatility-Normalized Volume– for different portfolios

Normalized Volume N=4					
Volatility			Implied Volatility		
Portfolio	Coefficient	p-value	Portfolio	Coefficient	p-value
1	0.00413*	0.08	1	-0.02312*	0.04
2	0.01213*	0.01	2	0.03068*	0.03
3	0.01296*	0.01	3	-0.00603	0.68
4	0.00803*	0.08	4	0.00922	0.59

* indicates statistical significance at 10 % level

Table 3.6 and 3.7 show the relationship between volume(Table3.6) or normalized volume (Table 3.7) and volatility for different portfolios. Portfolio 1 includes the smallest volume and Portfolio 4 includes the largest volume.

In these two tables, this chapter performs a time-series regression using the equation below and presents the results for β_i and θ_i.

Realised-volatility proxy:

$$Vol_{i,t} = \alpha_i + \sum_{j=1}^{n} \rho_{ij} Vol_{i,t-j} + \beta_i Activity_{i,t} + \eta_{it} \tag{3.19}$$

Implied volatility:

$$IV_{it} = \omega_i + \sum_{j=1}^{n} \lambda_{ij} IV_{i,t-j} + \theta_i Activity_{i,t} + \mu_{it} \tag{3.20}$$

where $Vol_{i,t}$ is realized volatility and IV_{it} is implied volatility. $Activity_{i,t}$ is volume ($Vlm_{i,t}$) or normalized volume $nv_{i,t}$.

Table 3.8: Results of Volatility/Implied Volatility-Order Flow– for different portfolios

Order Flow					
Volatility			Implied Volatility		
Portfolio	Coefficient	p-value	Portfolio	Coefficient	p-value
1	-1.12158*	0.05	1	-3.12501*	0.09
2	-0.01904	0.98	2	6.63047	0.11
3	2.32461*	0.05	3	6.80766*	0.10
4	1.86541*	0.00	4	2.36340	0.26

* indicates statistical significance at 10 % level

Table 3.8 shows the volatility - order flow relationship for OF1 to OF4, where OF1 include the highest selling pressure, and OF4 has the highest buying pressure.

In this table, this chapter performs a time-series regression using the equation below and presents the results for β_i and θ_i.

Realised-volatility proxy:

$$Vol_{i,t} = \alpha_i + \sum_{j=1}^{n} \rho_{ij} Vol_{i,t-j} + \beta_i Activity_{i,t} + \eta_{it} \tag{3.21}$$

Implied volatility:

$$IV_{it} = \omega_i + \sum_{j=1}^{n} \lambda_{ij} IV_{i,t-j} + \theta_i Activity_{i,t} + \mu_{it} \tag{3.22}$$

where $Vol_{i,t}$ is realized volatility and IV_{it} is implied volatility. $Activity_{i,t}$ is adjusted order flow $y_{i,t}$.

Table 3.9: Regression Results of Volatility/Implied Volatility-Order Flow Dis-aggregated by the Customer Type

Asset Manager						Corporate					
Volatility			Implied Volatility			Volatility			Implied Volatility		
Portfolio	Coefficient	p-value	Portfolio	Coefficient	p-value	Portfolio	Coefficient	p-value	Portfolio	Coefficient	p-value
1	-3.50595*	0.00	1	-0.51458	0.80	1	-1.04127	0.58	1	-4.45794	0.21
2	-1.35514	0.57	2	-25.39360*	0.00	2	-11.19615*	0.00	2	23.19682	0.14
3	2.54250*	0.00	3	-0.03906	0.97	3	-14.71994*	0.07	3	-14.01092*	0.00
Hedge Fund						Private Client					
Volatility			Implied Volatility			Volatility			Implied Volatility		
Portfolio	Coefficient	p-value	Portfolio	Coefficient	p-value	Portfolio	Coefficient	p-value	Portfolio	Coefficient	p-value
1	-0.87632	0.43	1	-0.69812	0.76	1	-2.80929	0.16	1	5.84977	0.14
2	2.77824	0.38	2	7.92380	0.17	2	17.34210*	0.02	2	48.02740*	0.00
3	2.35528*	0.04	3	-4.42696*	0.00	3	13.92305*	0.00	3	0.17448	0.94

* indicates statistical significance at 10 % level

Table 3.9 shows the volatility-order flow relationship for each customer. Here we show 4 kinds of customers: Asset Manager (AM), Hedge Fund (HF), Corporate (Co), and Private Clients (PC). In this table, this chapter performs a time-series regression using the equation below and presents the results for β_i.

$$Vol_{i,t} or (IV_{it}) = \alpha_i + \sum_{j=1}^{n} \rho_{ij} Vol_{i,t-j} + \beta_i Activity_{i,t} + \eta_{it} \tag{3.23}$$

where $Vol_{i,t}$ is realized volatility and IV_{it} is implied volatility. $Activity_{i,t}$ is adjusted order flow $y_{i,t}$.

Table 3.10: Regression with Dummy Variable Results of Volatility/Implied Volatility-Volume

Volume					
Volatility with Dummy Variable			Implied Volatility		
Portfolio	Coefficient	p-value	Portfolio	Coefficient	p-value
1	2.85050*	0.04	1	-1.77806	0.72
2	1.76472*	0.01	2	5.18453*	0.04
3	0.50007*	0.01	3	0.66184*	0.01
4	0.00189	0.97	4	0.09061	0.28

* indicates statistical significance at 10 % level

Table 3.11: Regression with Dummy Variable Results of Volatility/Implied Volatility-Order Flow

Order Flow					
Volatility with Dummy Variable			Implied Volatility		
Portfolio	Coefficient	p-value	Portfolio	Coefficient	p-value
1	-0.75767	0.19	1	-1.92219	0.31
2	0.38346	0.68	2	9.22016*	0.02
3	2.09892*	0.07	3	5.29263	0.20
4	1.71026*	0.00	4	1.36547	0.51

* indicates statistical significance at 10 % level

Table 3.10 and 3.11 show the results of volatility and volume/order flow with a financial crisis dummy variable. These two tables use the equation below and show the results of β_i and θ_i.
Realized-volatility proxy:

$$Vol_{i,t} = \alpha_i + \sum_{j=1}^{n} \rho_{ij} Vol_{i,t-j} + \beta_i Activity_{i,t} + \varphi D_{i,t} + \eta_{it} \tag{3.24}$$

Implied volatility:

$$IV_{it} = \omega_i + \sum_{j=1}^{n} \lambda_{ij} IV_{i,t-j} + \theta_i Activity_{i,t} + \varphi D_{i,t} + \mu_{it} \tag{3.25}$$

where $Activity_{i,t}$ is either volume ($Vlm_{i,t}$), or adjusted order flow $y_{i,t}$. $D_{i,t}$ is the dummy variable which equals 1 during the financial crisis period, otherwise equals 0. This chapter does the regression with dummy variables by using the portfolios (V1-V4 and OF1-OF4), so the i in all these equations indicates each portfolio.

Table 3.12: SUR Regression Results of Volatility/Implied Volatility and Volume

Volume									
Volatility					Implied Volatility				
Equation	Coefficient	p-value	chi2	P>chi2	Equation	Coefficient	p-value	chi2	P>chi2
1	3.49598	0.01	68.5	0.00	1	4.14031	0.36	2094.9	0.00
2	2.05960	0.00	33.2	0.00	2	4.18744	0.08	796.9	0.00
3	0.43706	0.01	39.0	0.00	3	0.89750	0.00	4253.9	0.00
4	-0.01184	0.81	10.6	0.06	4	0.17970	0.01	3803.2	0.00

Table 3.13: SUR Regression Results of Volatility/Implied Volatility and Order Flow

Order Flow									
Volatility					Implied Volatility				
Equation	Coefficient	p-value	chi2	P>chi2	Equation	Coefficient	p-value	chi2	P>chi2
1	0.09459	0.83	32.7	0.00	1	-3.27591	0.07	625.5	0.00
2	0.33337	0.69	33.5	0.00	2	4.81651	0.22	588.4	0.00
3	1.15092	0.21	11.7	0.04	3	7.66091	0.05	907.1	0.00
4	0.89084	0.04	7.4	0.19	4	2.14724	0.29	601.2	0.00

Table 3.12 and Table 3.13 show the SUR regression results for volatility - volume and volatility - order flow. These two tables use the equation below and show the results of β_i and θ_i.
Realized-volatility proxy:

$$Vol_{i,t} = \alpha_i + \sum_{j=1}^{n} \rho_{ij} Vol_{i,t-j} + \beta_i Activity_{i,t} + \eta_{it}, i = 1, 2, 3, 4 \tag{3.26}$$

Implied volatility:

$$IV_{it} = \omega_i + \sum_{j=1}^{n} \lambda_{ij} IV_{i,t-j} + \theta_i Activity_{i,t} + \mu_{it}, i = 1, 2, 3, 4 \tag{3.27}$$

where $Activity_{i,t}$ is either volume ($Vlm_{i,t}$), or adjusted order flow $y_{i,t}$. The i in both these equations indicates each portfolio.

Appendices for Chapter 3

3A Transfer Weekly Volatility into Monthly Volatility

3A.1 Normal Volatility

Under normal conditions, we often use standard deviation as a measure of volatility, and when we want to calculate the monthly volatility, we first need to calculate the monthly return. In this chapter, we use equation (5) to calculate the logarithmic return to instead of the simple return, which can also be expressed as:

$$R_{i,t} = log(p_{i,t}) - log(p_{i,t-1}) = log\frac{p_{i,t}}{p_{i,t-1}} = log\frac{p_{i,t-1}(1+r_{t-1})}{p_{i,t-1}} = log(1+r_{t-1}) \quad (3.28)$$

where $r_{i,t-1}$ is simple return at weekly $t-1$ of currency i. Because the monthly (1+ simple return) can be calculated as the product of four (1+ weekly returns), the monthly logarithmic return can be expressed below according to the simple return:

$$\begin{aligned} R_{i,T} = log(1+r_T) &= log[(1+r_t)(1+r_{t+1})(1+r_{t+2})(1+r_{t+3})] \\ &= log(1+r_t) + log(1+r_{t+1}) + log(1+r_{t+2}) + log(1+r_{t+3}) \\ &= R_{i,t} + R_{i,t+1} + R_{i,t+2} + R_{i,t+3} \end{aligned} \quad (3.29)$$

where $R_{i,T}$ is monthly log return of currency i and r_T is monthly simple return of currency $i$the variances. Secondly, because weekly log returns are uncorrelated and of the same variance, variance can be added. In order to this reason, we can use the monthly log return to calculate the monthly variance:

$$Var(R_{i,T}) = Var(R_{i,t}) + Var(R_{i,t+1}) + Var(R_{i,t+2}) + Var(R_{i,t+3}) = 4 \times \sigma_{i,t}^2 \quad (3.30)$$

where $Var(R_{i,T})$ is the variance of monthly log return.$\sigma_{i,t}^2$ is the weekly variance. According to the variance, we can further calculate the standard deviation, which is also the expression of volatility:

$$Sd(R_{i,T} = \sqrt{Var(R_{i,T})} = \sqrt{4 \times \sigma_{i,t}^2} = 2\sigma_{i,t} \quad (3.31)$$

where $Sd(R_{i,T})$ is the monthly standard deviation of return and the $\sigma_{i,t}$ is the weekly standard deviation of return. According to the equation above, we can get that the monthly volatility is twice the weekly volatility.

3A.2 Volatility in this chapter

The data used in this chapter is weekly. Here we want to calculate the monthly volatility according to the model we set up. Firstly, we still need to use the equation above to calculate the monthly return. Secondly, we can rewrite this equation to have the residual term expression:

$$\epsilon_{it} = R_{i,t} - \sum_{j=1}^{1,4,8,12} \beta_j R_{i,t-j} \tag{3.32}$$

Thirdly, we use monthly return $R_{i,T}$ to replace the weekly return $R_{i,t}$, and get the new equation:

$$\epsilon_{iT} = R_{i,T} - \beta_1 R_{i,T-1} - \beta_4 R_{i,T-4} - \beta_8 R_{i,T-8} - \beta_1 2 R_{i,T-12} \tag{3.33}$$

Fourthly, we get the equation below:

$$\begin{aligned} \epsilon_{iT} &= R_{i,t} + R_{i,t+1} + R_{i,t+2} + R_{i,t+3} \\ &-\beta_1(R_{i,t-1} + R_{i,t} + R_{i,t+1} + R_{i,t+2} \\ &-\beta_4(R_{i,t-4} + R_{i,t-3} + R_{i,t-2} + R_{i,t-1} \\ &-\beta_8(R_{i,t-8} + R_{i,t-7} + R_{i,t-6} + R_{i,t-5} \\ &-\beta_{12}(R_{i,t-12} + R_{i,t-11} + R_{i,t-10} + R_{i,t-9}) \end{aligned} \tag{3.34}$$

Finally, we can write the monthly volatility below:

$$|\epsilon_{iT}| = |\sum_{a=0}^{3} R_{i,t+a} - \beta_1 \sum_{b=-1}^{2} R_{i,t+b} - \beta_4 \sum_{c=-4}^{-1} R_{i,t+c} - \beta_8 \sum_{d=-8}^{-5} R_{i,t+d} - \beta_{12} \sum_{e=-12}^{-8} R_{i,t+e}| \tag{3.35}$$

3B Different Volatility

Volatility is the degree of fluctuation used to measure the price of financial assets, which represents how large an asset's price swings around the mean price. It can imply the risk level of financial assets. The higher the volatility, the greater the possible risk of securities. From the economic view, volatility appears mainly because of three reasons. Firstly, the systematic risk which is the effect of the macroeconomic factors on an industrial sector. Secondly, the non-systematic risk is the impact of a specific event on an enterprise. Thirdly, the effect that the changes in investors' psychological state or expectations have on stock prices. Volatility is a statistical measure of the dispersion of returns, and there are several ways to measure it, including beta coefficients, option pricing models, and standard deviations of returns. Researchers mainly classified the volatilities into four types: realised volatility, historical volatility, forecasting volatility, and implied volatility. Different types have different models to calculate it. This chapter mainly focuses on the realised and implied ones, and in the following part, more details are introduced.

Implied volatility (IV) refers to an indicator that reflects the market's view of the possibility of changes in the price of a given security. It displays as a percentage, which reports the risk level perceived by traders. IV can show the expected change of a specific stock index, stock, commodity or major currency over a specified period of time. However, IV is only a prediction of the expected market trend; it doesn't predict the direction in which the price change will proceed. In other words, implied volatility represents the expected range of potential results and the uncertainty that the underlying assets may rise or fall. High implied volatility indicates that traders are more likely to expect large price fluctuations, while low implied volatility indicates that the market expects relatively mild price fluctuations. Implied volatility can help traders measure market sentiment because it widely describes the level of perceived risk. Furthermore, implied volatility can be used as a foreign exchange signal, largely due to the inherent mean-reversion characteristics of major currencies. Implied volatility is the volatility determined by the option market price, which is the true mapping of the market price. In the meantime, the effective market price is the product of the balance between supply and demand and the result of the game between the buyer and the seller. For this reason, the implied volatility reflects the market's view on the volatility of the target product, which has a very useful application in option trading. Since implied volatility is embedded in an option's price, we calculate the implied volatility by putting all four other known quantities into the BS model formula, which was first proposed in 1973Scholes 1973:

$$C = S_t N(d_1) - Ke^{-rt} N(d_2) \tag{3.36}$$

where

$$d_1 = \frac{ln\frac{S_t}{K} + (r + \frac{\sigma_v^2}{2})t}{\sigma_s \sqrt{t}} \tag{3.37}$$

and

$$d_2 = d_1 - \sigma_s \sqrt{t} \tag{3.38}$$

In this model, C is the option price, S equals the current stock price, K is the exercise price, r is the risk-free rate, t equals the time to maturity, and N is a normal distribution. Once all the above parameters can be observed, the implied volatility (σ_s) can be derived.

We make a comparison of these two different kinds of volatility, which is summarised in Table 3.14. It can be found that because we are going to calculate the fluctuation of foreign exchange price, the current exchange price term is compulsory in both of them. For volatility, it also needs the exchange price of the previous time. And for implied volatility, it is composed of the call option price, exercise price, risk-free rate and the time to maturity. After comparing the components, we can find that the volatility calculated by ourselves pays attention to the past price and the implied volatility focuses on the prices and time, which will lead to the future performance of the price. This makes the volatility express the historical volatility, and the implied volatility leads to the future volatility.

Table 3.14: Components of Different Kinds of Volatility

	Volatility	Implied Volatility
exclusive	last week exchange price	call option price exercise price risk-free rate time to maturity
common	current exchange price	

3C Data Description

In 3C.1, we show how our data change over time. And the diagrams in 3C.2 show the distribution of each data set.

3C.1 Time Series Plots

Figure 3.3: Volume and Order Flow-original

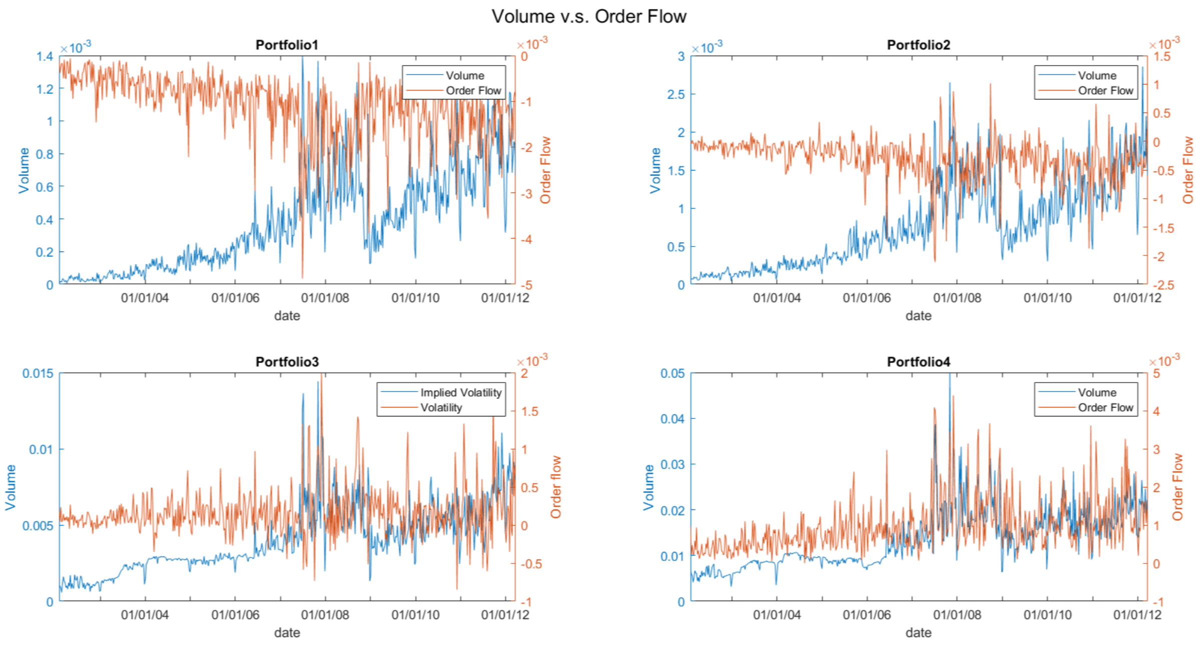


Figure 3.3 shows the time series plots of volume and order flow. The volume and order flow data here has been divided by 1000.

Figure 3.4: Volume vs Order flow – using 4 weeks rolling windows

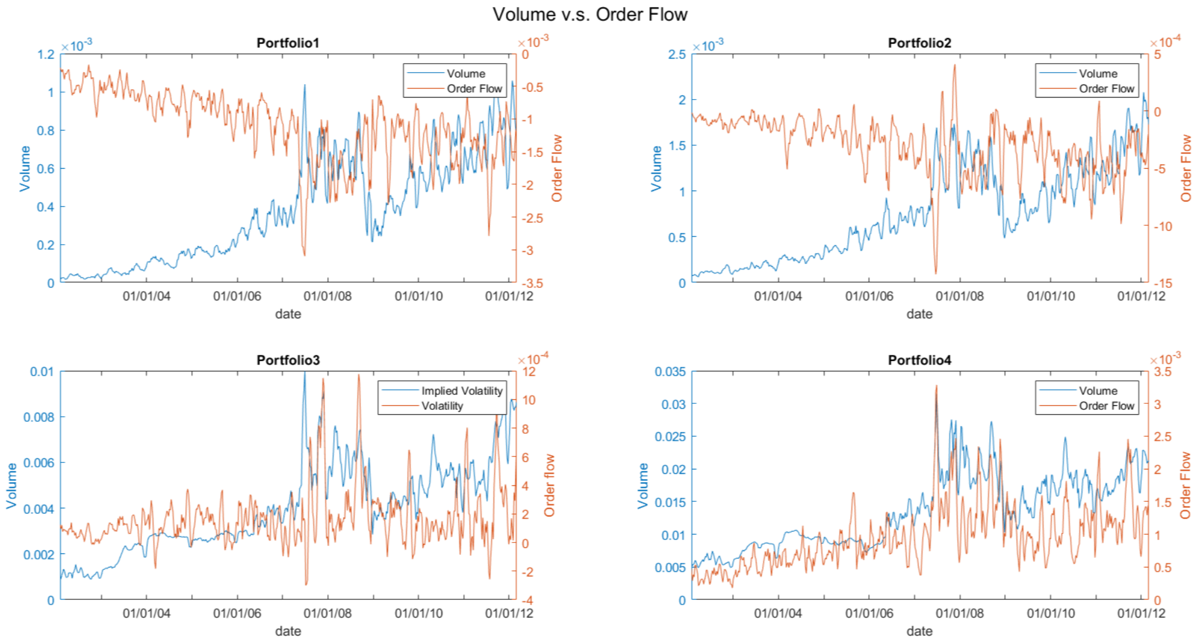


Figure 3.4 uses 4 weeks rolling windows to re-create the time series plots of volume and order flow, which aims to visually observe the characteristics of these two datasets.

Figure 3.5: RV, Std. and IV portfolios sorted by order flow – using 4 weeks rolling windows

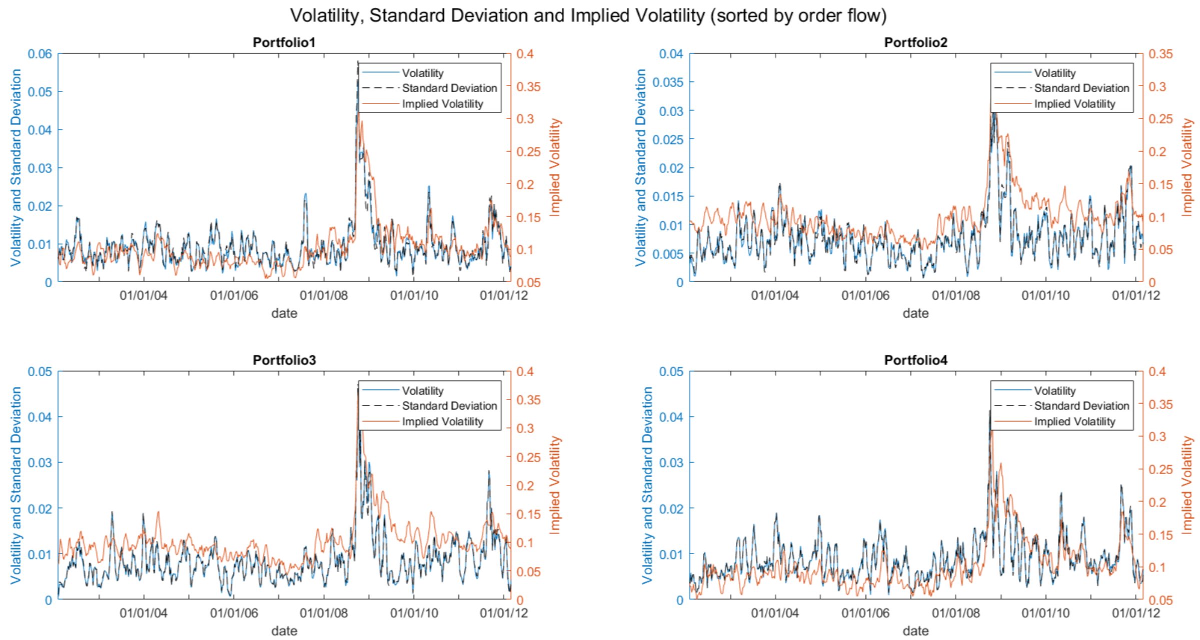


Figure 3.6: RV, Std. and IV portfolios sorted by volume – using 4 weeks rolling windows

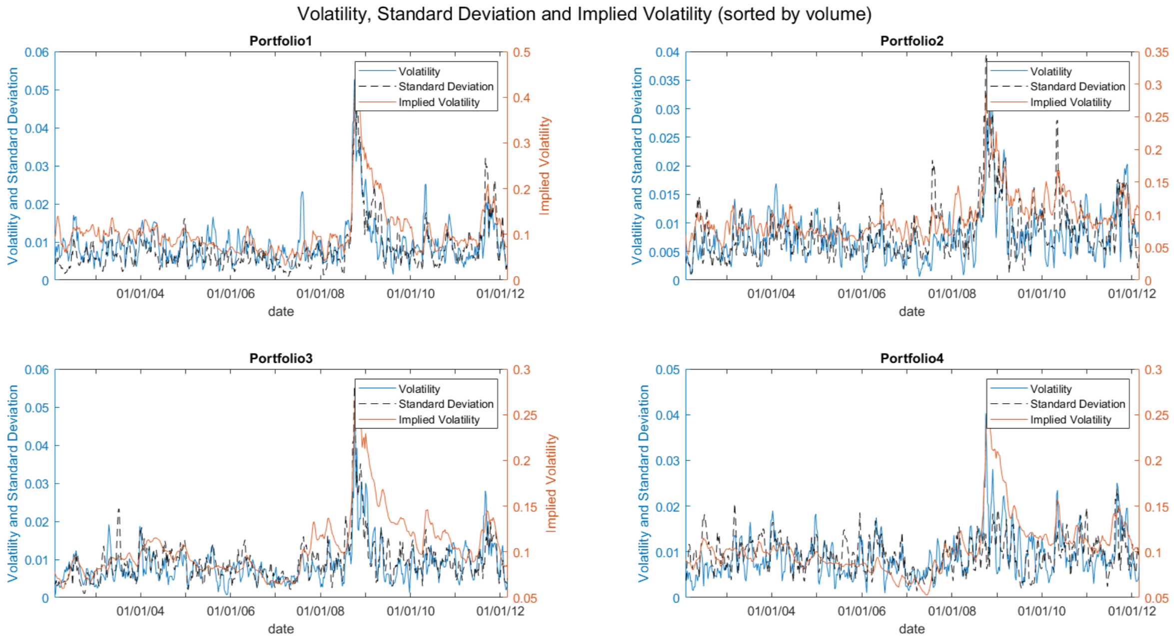


Figure 3.5 and Figure 3.6 use 4 weeks rolling windows to separately plot the time series lines of realized volatility, standard deviation of return and implied volatility portfolios. In this chapter, we use equation (6) to calculate the volatility, which has been seen as realised volatility in these Figures. Using the standard deviation of exchange price return rate as a benchmark helps us to check the accuracy of realised volatility. The implied volatility has been divided by 100. In order to guarantee the volatility can be matched with volume and order flow at each date t, this chapter uses two ways to create portfolios and separately plots the lines of volatility, standard deviation/implied volatility, where one is sorted by volume(Figure 3.6) and the other one is sorted by order flow(Figure 3.5).

3C.2 Histogram of Data Distribution

Figure 3.7: Histogram of Volume

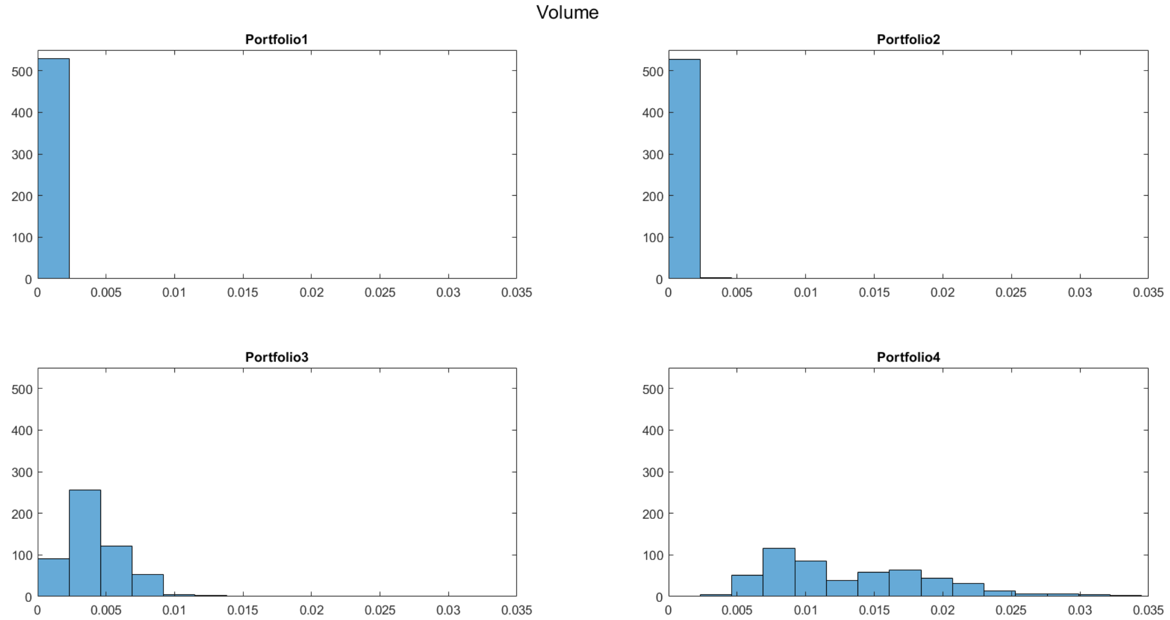


Figure 3.8: Histogram of Order Flow

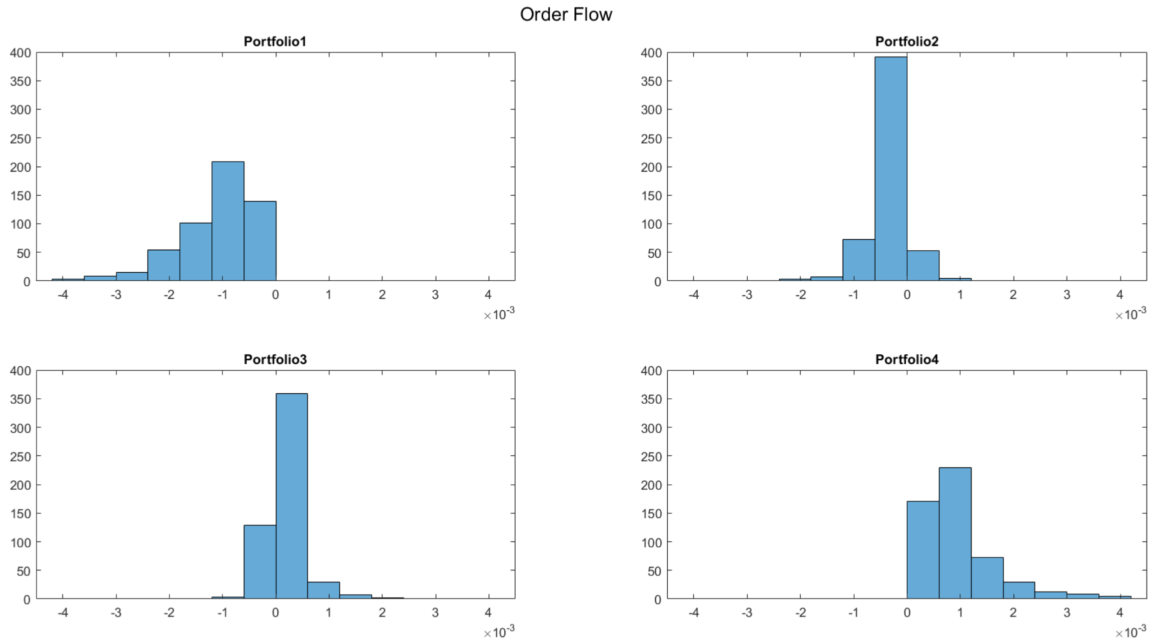


Figure 3.7 and Figure 3.8 show the distribution of volume and order flow. We use the data divided by 1000 to replace the original data sets to create these histograms.

Figure 3.9: Histogram of Volatility sorted by Volume

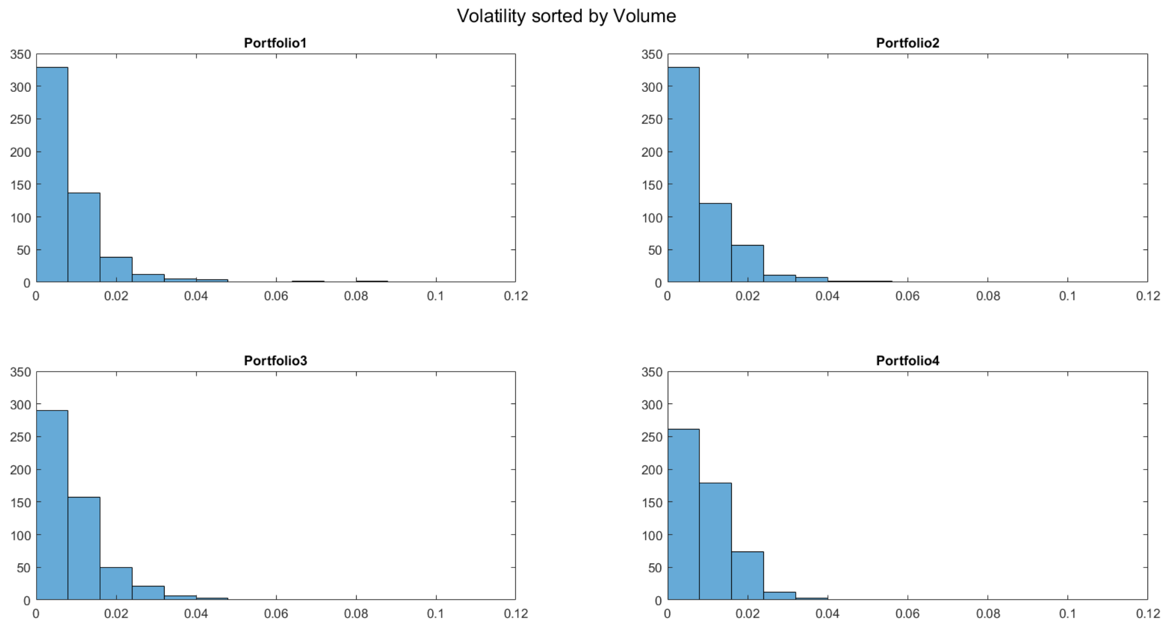


Figure 3.10: Histogram of Volatility sorted by Order Flow

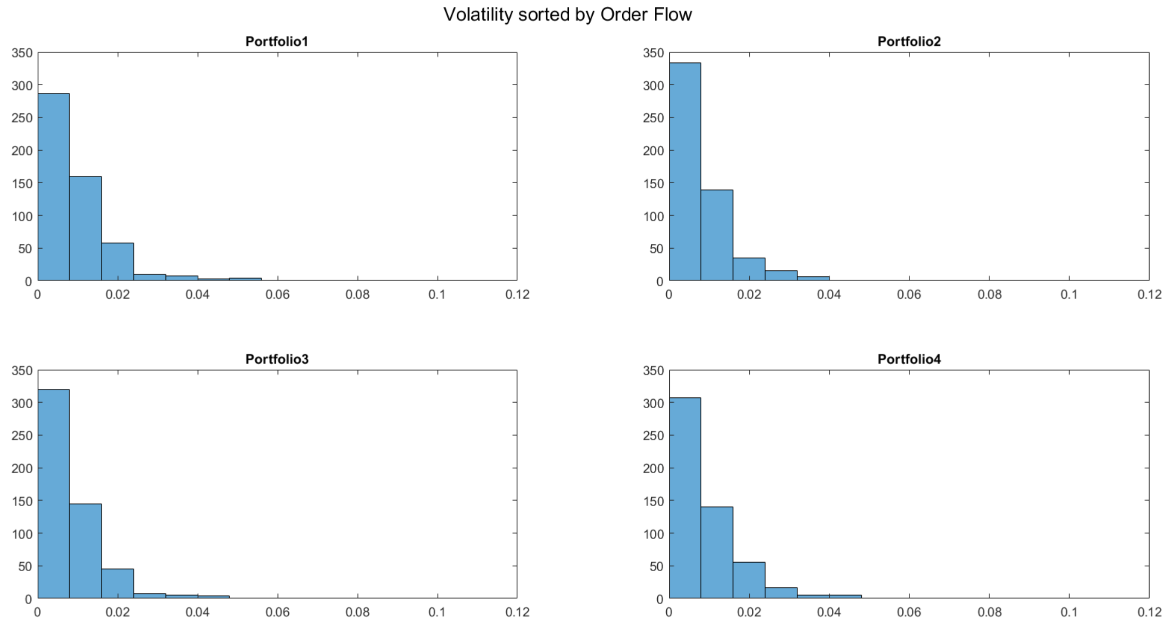


Figure 3.9 and Figure 3.10 show the distribution of volatility data. We divided the overall data into 4 portfolios. Same as when creating time series, Figure 3.9 and Figure 3.10 also use two ways to create portfolios to maintain the volatility/implied volatility and volume/ order flow can be corresponded to each other at date t.

Figure 3.11: Histogram of Implied Volatility sorted by Volume

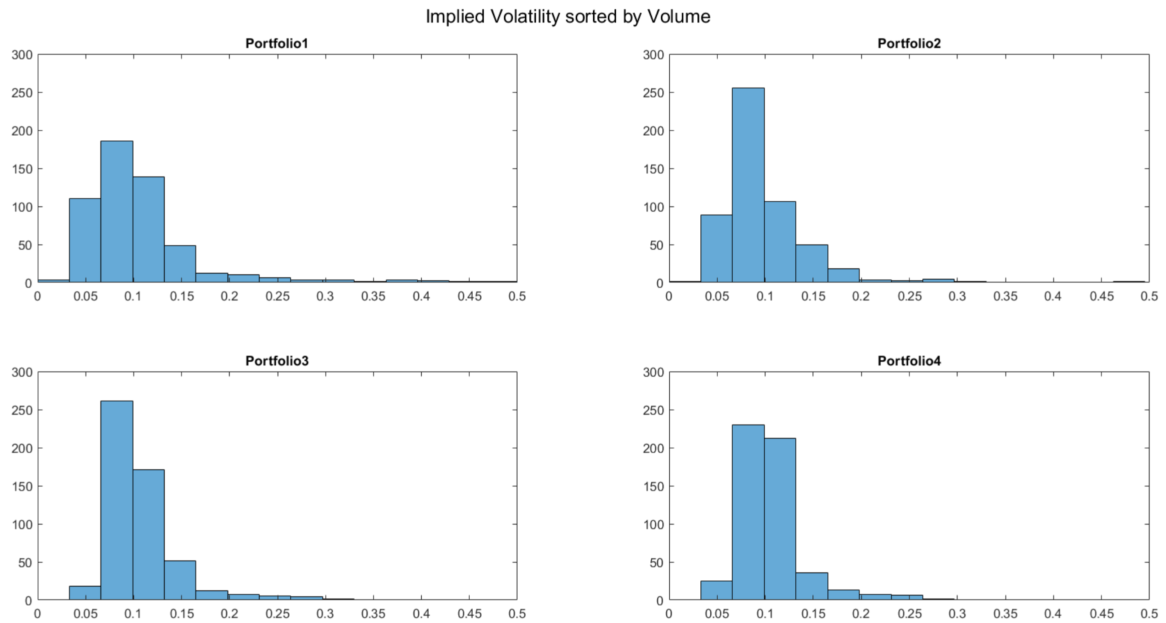


Figure 3.12: Histogram of Implied Volatility sorted by Order Flow

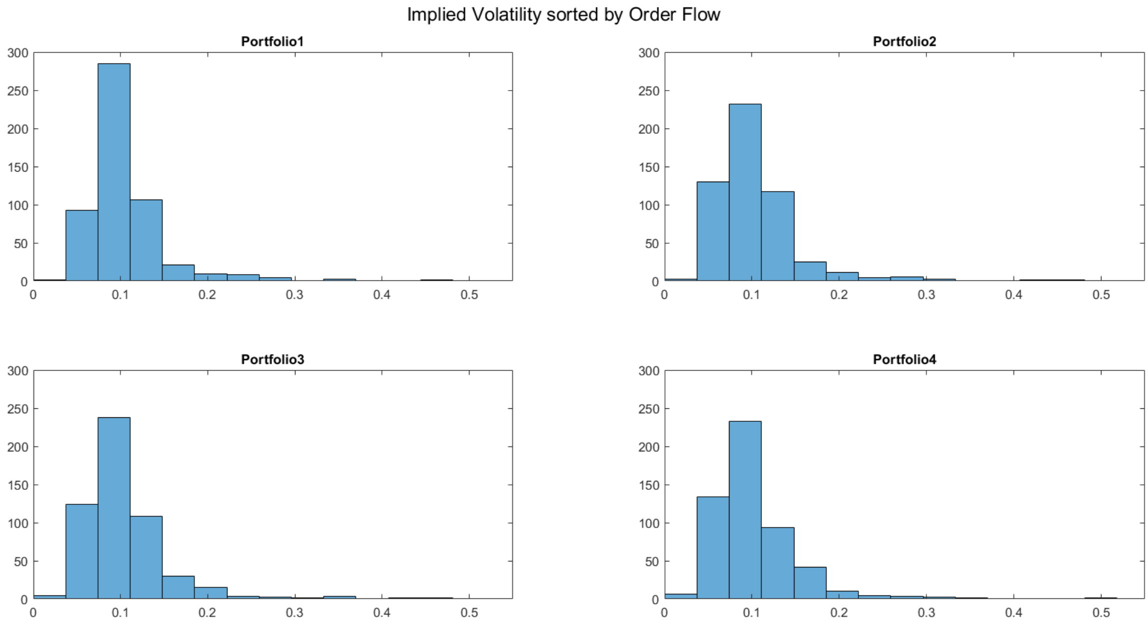


Figure 3.11 and Figure 3.12 exhibit the distribution of implied volatility data, and here we still divided the whole data into 4 portfolios by two ways. One is sorted by volume(Figure 3.11) and the other one is sorted by order flow(Figure 3.12). The implied volatility used here has been divided by 100.

3C.3 Relationship Plots

Figure 3.13: Volatility-Volume

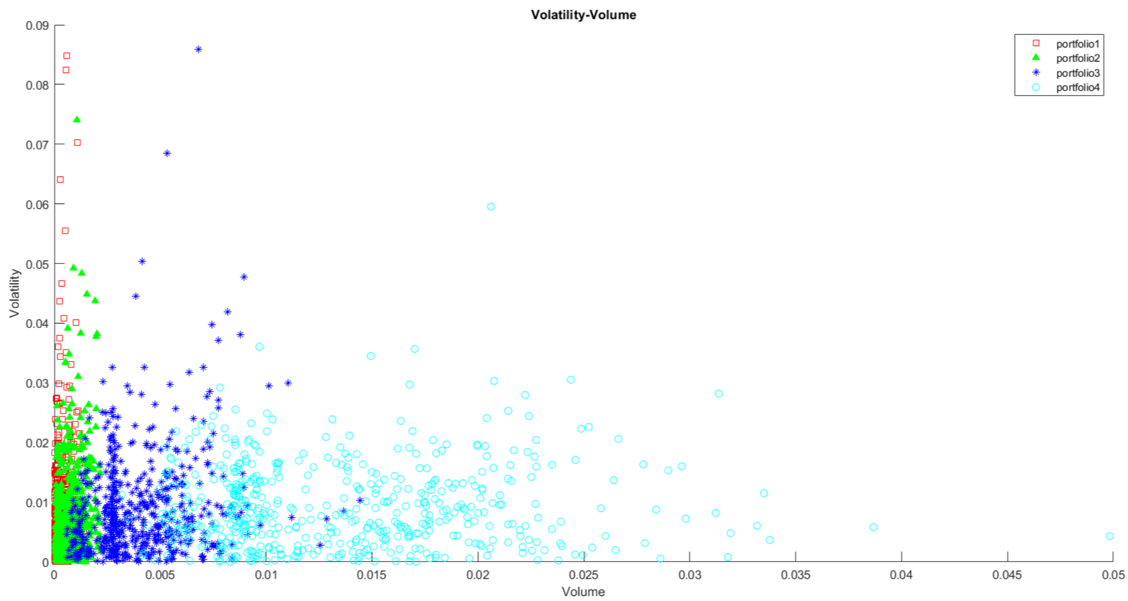
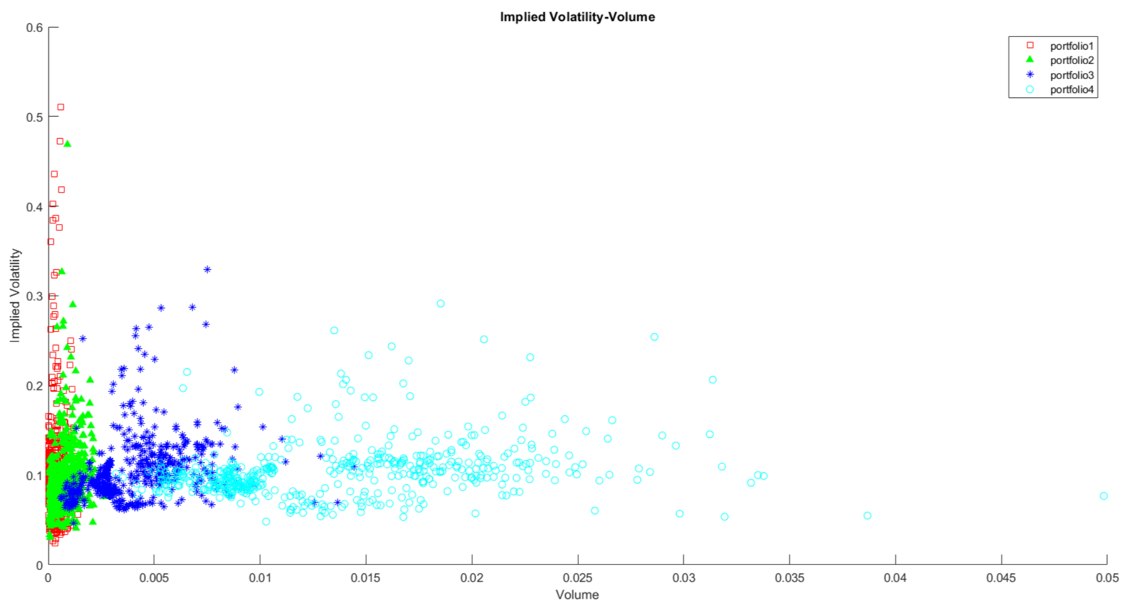


Figure 3.14: Implied Volatility-Volume



Appendix 3C.3 shows the scatter plots of the relationship between volatility/implied volatility and original volume. The implied volatility has been divided by 100, and the volume and order flow have been divided by 1000.

Figure 3.15: Log(Ratio of IV/VOL)- Log (Volume)

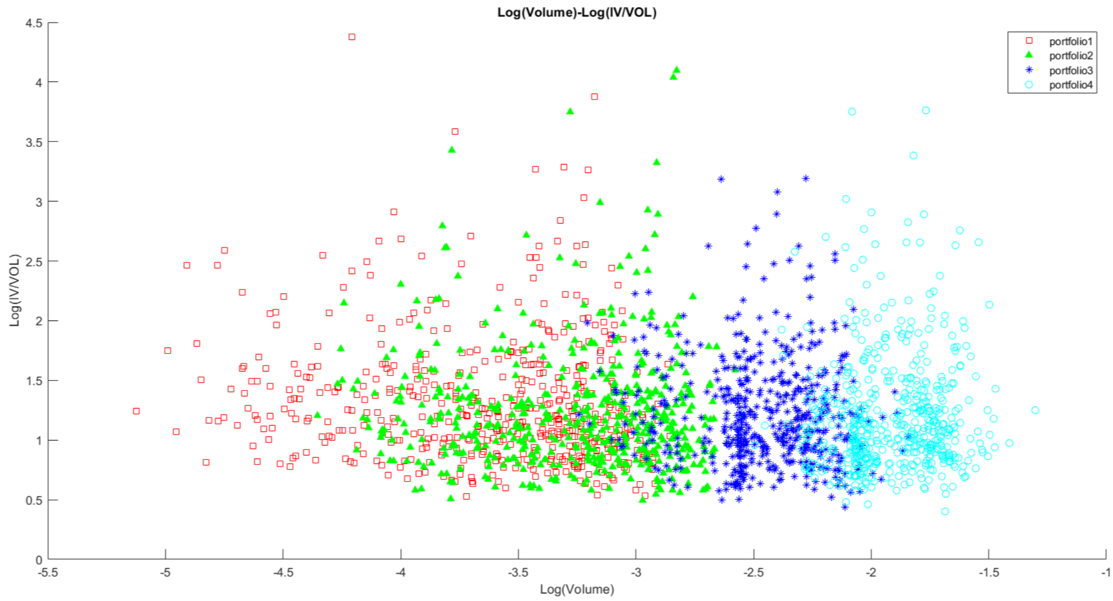


Figure 3.15 is the relationship scatter plot of log(Ratio of IV/VOL) and log of volume. The y-axis of this diagram shows the ratio of implied volatility divided by volatility. The volume used in this diagram has been divided by 1000.

Figure 3.16: Log(Ratio of IV/VOL with Dummy Variable)- Log (Volume)

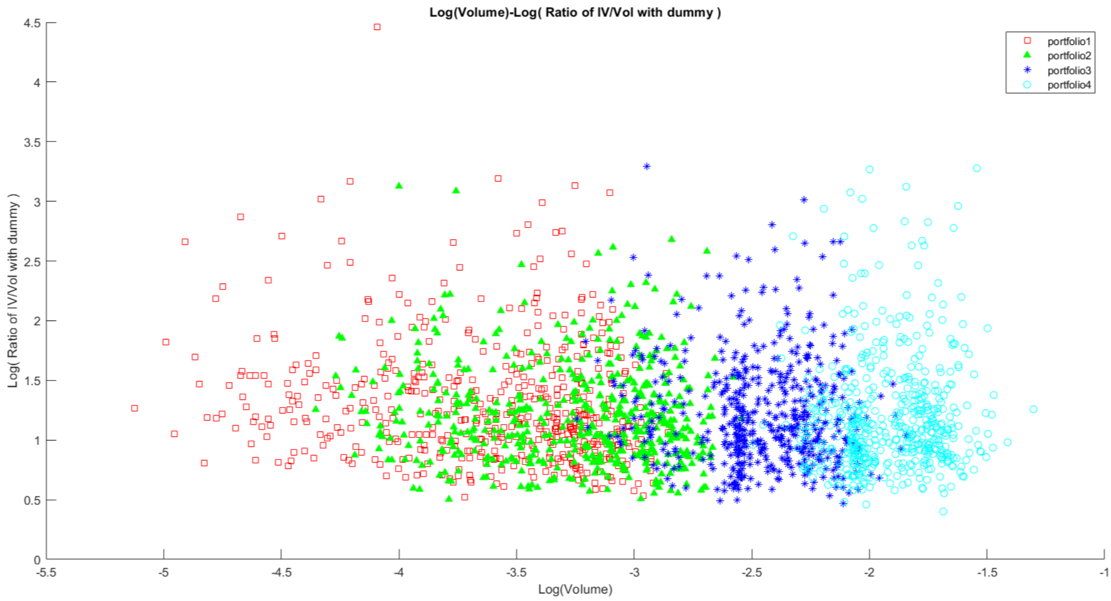


Figure 3.16 shows the relationship between the log of the ratio and the log of the volume. The ratio in this diagram is implied volatility divided by volatility with dummy variable.

3D Empricial Results

3D.1 Stationary Test-ADF test

Table 3.15: Unit Roots Test for Return/IV-Volume

UNIT ROOTS TEST								
Vol/IV-Volume								
Volume			Return			Implied Volatility		
	z	P>z		z	P>z		z	P>z
O1	-6.808	0	P1	-23.168	0	P1	-6.682	0
O2	-6.719	0	P2	-22.689	0	P2	-10.874	0
O3	-7.636	0	P3	-22.825	0	P3	-3.974	0
O4	-8.492	0	P4	-23.455	0	P4	-4.169	0

Table 3.16: Unit Roots Test for Return/IV-Order Flow

UNIT ROOTS TEST								
Vol/IV-Order Flow								
Order Flow			Return			Implied Volatility		
	z	P>z		z	P>z		z	P>z
O1	-14.459	0	P1	-21.229	0	P1	-9.752	0
O2	-16.33	0	P2	-22.171	0	P2	-10.62	0
O3	-17.832	0	P3	-23.408	0	P3	-8.746	0
O4	-15.109	0	P4	-23.167	0	P4	-10.246	0

Table 3.15and 3.16 show the results of stationary test. This chapter firstly guarantees the stationarity of our portfolios.

3D.2 Results of Different Rolling Windows

In order to keep the correctness and rigour, this chapter also does the regression for the relationship between volatility and volume and volume with return when the rolling average window equals 12. Because this chapter used weekly data, when the rolling window equals 12, we can see that as the seasonal average. The results when N equals 12 have been shown in the main text, and we can find that portfolios 1, 3, and 4 in volatility get significant results, and there is no portfolio that is significant in implied volatility. For volatility, per unit normalised volume of portfolio 1 can increase volatility by 0.004 units, and per unit normalised volume of portfolios 3 and 4 can positively affect volatility by 0.01 and 0.008 units. We can find that when the rolling window extends, the results are a little different from before. The influence of normalised volume on implied volatility is not as strong as on volatility.

Table 3.17: Results of Volatility/Implied Volatility-Normalized Volume-N=12

Volume with Return N=12									
Volatility					Implied Volatility				
Portfolio	B	p-value1	C	p-value2	Portfolio	B	p-value1	C	p-value2
1	-0.309	0.02	0.004*	0.10	1	-1.310	0.01	-0.003	0.77
2	-0.300	0.39	0.007	0.12	2	-1.680	0.12	0.001	0.94
3	0.554	0.09	0.010*	0.02	3	1.905	0.07	0.009	0.51
4	0.794	0.00	0.008*	0.03	4	1.649	0.01	0.007	0.62

* indicates statistical significance at 10 % level

Table 3.17 shows the normalized volume and volatility relationship for different portfolios. In this table, the chapter performs a time-series regression using the equation below and reports the results forρ_{ij}, and β_i. This table shows the results when the rolling average equals 12.

$$Vol_{i,t} or IV_{it} = \alpha_i + \sum_{j=1}^{n} \rho_{ij} Vol_{i,t-j} + \beta_i Activity_{i,t} + \eta_{it} \tag{3.39}$$

where $Vol_{i,t}$ is realized volatility and IV_{it} is implied volatility. $Activity_{i,t}$ is normalized volume $nv_{i,t}$.

3D.3 Regression Results

Table 3.18-3.23 show the results when using different lags. In this table, the chapter performs a time-series regression using the equation below and reports the results for β_i and θ_i.

Realised-volatility proxy:

$$Vol_{i,t} = \alpha_i + \sum_{j=1}^{n} \rho_{ij} Vol_{i,t-j} + \beta_i Activity_{i,t} + \eta_{it} \tag{3.40}$$

Implied volatility:

$$IV_{it} = \omega_i + \sum_{j=1}^{n} \lambda_{ij} IV_{i,t-j} + \theta_i Activity_{i,t} + \mu_{it} \tag{3.41}$$

where $Vol_{i,t}$ is realized volatility and IV_{it} is implied volatility. $Activity_{i,t}$ is volume $Vlm_{i,t}$, normalized volume $nv_{i,t}$ and adjusted order flow $y_{i,t}$.

Table 3.18: Regression Results of Volume and Volatility with Different Lags

Vol-Volume								
Portfolio	lag	beta(i)	p-value	N	R-sq	Adj-R-sq	95% conf. interval	
1	4	2.70166	0.04*	526	0.21921	0.211702	0.176436	5.226886
	8	2.74300	0.03*	522	0.226988	0.2134	0.195975	5.290033
	12	2.67513	0.04*	518	0.227893	0.207978	0.098395	5.251865
	1,4,8,12	3.49945	0.01*	518	0.142638	0.134265	0.821339	6.177553
2	4	1.94540	0.00*	526	0.094694	0.085989	0.661186	3.229622
	8	1.56526	0.02*	522	0.139057	0.123923	0.292634	2.837887
	12	1.49938	0.02*	518	0.144238	0.122165	0.213437	2.785315
	1,4,8,12	2.00071	0.00*	518	0.074593	0.065556	0.68902	3.312405
3	4	0.60164	0.00*	526	0.12007	0.111609	0.25965	0.943635
	8	0.54935	0.00*	522	0.142937	0.127872	0.207351	0.891347
	12	0.55400	0.00*	518	0.162446	0.140843	0.211076	0.896924
	1,4,8,12	0.61965	0.00*	518	0.104933	0.096192	0.270086	0.969223
4	4	0.02170	0.66	526	0.00723	-0.00232	-0.07541	0.118816
	8	0.04003	0.42	522	0.038479	0.021577	-0.05712	0.137167
	12	0.03514	0.49	518	0.040096	0.015337	-0.06383	0.134107
	1,4,8,12	0.02567	0.61	518	0.027114	0.017613	-0.07193	0.123267

* indicates statistical significance at 10 % level

Table 3.19: Regression Results of Volume and Implied Volatility with Different Lags

IV-Volume								
Portfolio	lag	beta(i)	p-value	N	R-sq	Adj-R-sq	95% conf. interval	
1	4	1.55130	0.73	526	0.751008	0.748614	-7.34859	10.45118
	8	1.91220	0.68	522	0.752714	0.748367	-7.0787	10.9031
	12	1.05337	0.82	518	0.758113	0.751874	-7.95945	10.06619
	1,4,8,12	1.78507	0.71	518	0.727893	0.725236	-7.68832	11.25847
2	4	5.73656	0.02*	526	0.488425	0.483506	0.829854	10.64328
	8	5.15291	0.04*	522	0.492618	0.483699	0.232291	10.07353
	12	5.07082	0.04*	518	0.504367	0.491583	0.154223	9.987412
	1,4,8,12	6.05482	0.02*	518	0.468535	0.463345	1.022092	11.08756
3	4	0.69066	0.00*	526	0.911802	0.910954	0.239125	1.142197
	8	0.63631	0.01*	522	0.914462	0.912959	0.187031	1.085586
	12	0.57879	0.01*	518	0.916645	0.914495	0.130839	1.026741
	1,4,8,12	0.73744	0.00*	518	0.889628	0.88855	0.227947	1.246927
4	4	0.17798	0.01*	526	0.899049	0.898079	0.034986	0.320975
	8	0.17934	0.02*	522	0.899541	0.897775	0.034917	0.323761
	12	0.16548	0.03*	518	0.900326	0.897755	0.019419	0.311546
	1,4,8,12	0.13969	0.08*	518	0.87897	0.877788	-0.01915	0.298528

* indicates statistical significance at 10 % level

Table 3.20: Regression Results of Log of Volume and Volatility with Different Lags

Vol-Log of Volume								
Portfolio	lag	beta(i)	p-value	N	R-sq	Adj-R-sq	95% conf. interval	
1	4	0.00142	0.08*	526	0.217304	0.209778	-0.00015	0.002994
	8	0.00140	0.09*	522	0.224649	0.21102	-0.00021	0.003006
	12	0.00138	0.10*	518	0.22564	0.205666	-0.00028	0.003035
	1,4,8,12	0.00188	0.03*	518	0.139319	0.130914	0.000156	0.003601
2	4	0.00270	0.00*	526	0.094254	0.085545	0.000891	0.004508
	8	0.00195	0.04*	522	0.136731	0.121557	0.000133	0.003776
	12	0.00183	0.06*	518	0.14162	0.119479	-4.1E-05	0.003705
	1,4,8,12	0.00266	0.01*	518	0.072073	0.063012	0.000761	0.004568
3	4	0.00502	0.00*	526	0.118116	0.109637	0.002016	0.00803
	8	0.00435	0.01*	522	0.139578	0.124454	0.001312	0.007379
	12	0.00439	0.01*	518	0.158827	0.13713	0.001314	0.007463
	1,4,8,12	0.00526	0.00*	518	0.102894	0.094133	0.002133	0.008378
4	4	0.00065	0.68	526	0.007188	-0.00236	-0.00245	0.00375
	8	0.00116	0.46	522	0.038266	0.02136	-0.00194	0.004273
	12	0.00095	0.56	518	0.039828	0.015061	-0.00224	0.004145
	1,4,8,12	0.00067	0.68	518	0.026941	0.017439	-0.00248	0.00383

* indicates statistical significance at 10 % level

Table 3.21: Regression Results of Log of Volume and Implied Volatility with Different Lags

IV-Log of Volume								
Portfolio	lag	beta(i)	p-value	N	R-sq	Adj-R-sq	95% conf. interval	
1	4	0.00150	0.59	526	0.751089	0.748695	-0.00403	0.007033
	8	0.00204	0.48	522	0.752872	0.748528	-0.00362	0.007689
	12	0.00111	0.71	518	0.758156	0.751918	-0.00466	0.006866
	1,4,8,12	0.00139	0.65	518	0.727928	0.725272	-0.00467	0.007448
2	4	0.00647	0.07*	526	0.486515	0.481578	-0.0005	0.013447
	8	0.00517	0.15	522	0.490478	0.481522	-0.0019	0.012244
	12	0.00530	0.15	518	0.502404	0.489569	-0.00189	0.012493
	1,4,8,12	0.00693	0.06*	518	0.466314	0.461102	-0.00042	0.014283
3	4	0.00577	0.00*	526	0.911635	0.910785	0.00177	0.009769
	8	0.00552	0.01*	522	0.914402	0.912898	0.001526	0.009509
	12	0.00475	0.02*	518	0.916466	0.914312	0.000716	0.008793
	1,4,8,12	0.00576	0.01*	518	0.889195	0.888113	0.001163	0.010366
4	4	0.00548	0.02*	526	0.898966	0.897995	0.000909	0.010049
	8	0.00554	0.02*	522	0.899456	0.897689	0.000905	0.010172
	12	0.00511	0.03*	518	0.900241	0.897668	0.000389	0.009839
	1,4,8,12	0.00457	0.08*	518	0.878985	0.877803	-0.00057	0.009717

* indicates statistical significance at 10 % level

Table 3.22: Regression Results of Order Flow and Volatility with Different Lags

Vol-Order Flow								
Portfolio	lag	beta(i)	p-value	N	R-sq	Adj-R-sq	95% conf. interval	
1	4	-1.02779	0.06*	526	0.115369	0.106863	-2.09763	0.042058
	8	-1.08311	0.05*	522	0.142899	0.127833	-2.1525	-0.01371
	12	-1.13993	0.04*	518	0.144457	0.122389	-2.23362	-0.04624
	1,4,8,12	-1.12158	0.05*	518	0.087845	0.078937	-2.22786	-0.01531
2	4	-0.15289	0.87	526	0.100855	0.092209	-1.92691	1.621128
	8	-0.09082	0.92	522	0.116039	0.100501	-1.86595	1.68431
	12	-0.00883	0.99	518	0.120223	0.09753	-1.79864	1.780971
	1,4,8,12	-0.01904	0.98	518	0.076874	0.067859	-1.83047	1.792398
3	4	1.51365	0.18	526	0.103504	0.094884	-0.71888	3.746187
	8	1.46134	0.20	522	0.133576	0.118346	-0.75698	3.679668
	12	1.53490	0.18	518	0.142367	0.120246	-0.69144	3.761244
	1,4,8,12	2.32461	0.05*	518	0.054939	0.045709	0.043262	4.60595
4	4	1.72995	0.00*	526	0.051646	0.042527	0.693133	2.76677
	8	1.74731	0.00*	522	0.070287	0.053944	0.703886	2.790744
	12	1.77973	0.00*	518	0.077967	0.054184	0.729245	2.830209
	1,4,8,12	1.86541	0.00*	518	0.050492	0.04122	0.827597	2.903228

* indicates statistical significance at 10 % level

Table 3.23: Regression Results of Order Flow and Implied Volatility with Different Lags

IV-Order Flow								
Portfolio	lag	beta(i)	p-value	N	R-sq	Adj-R-sq	95% conf. interval	
1	4	-3.27849	0.07*	526	0.552516	0.548214	-6.83222	0.275236
	8	-3.15428	0.08*	522	0.57684	0.569401	-6.65226	0.343705
	12	-2.90919	0.11	518	0.58344	0.572695	-6.44006	0.621682
	1,4,8,12	-3.12501	0.09*	518	0.544242	0.539791	-6.75809	0.508076
2	4	6.61724	0.08*	526	0.55767	0.553417	-0.85662	14.0911
	8	7.14787	0.06*	522	0.562461	0.55477	-0.36815	14.66388
	12	7.34465	0.06*	518	0.56814	0.557001	-0.20512	14.89442
	1,4,8,12	6.63047	0.11	518	0.496844	0.49193	-1.4209	14.68184
3	4	4.84351	0.23	526	0.621542	0.617903	-3.08598	12.77301
	8	5.13085	0.20	522	0.634443	0.628017	-2.7444	13.00609
	12	5.58065	0.17	518	0.640463	0.631189	-2.30837	13.46967
	1,4,8,12	6.80766	0.10	518	0.60833	0.604505	-1.24312	14.85845
4	4	1.88022	0.34	526	0.546488	0.542128	-2.01529	5.775731
	8	2.01498	0.31	522	0.554822	0.546997	-1.88668	5.916643
	12	2.05826	0.30	518	0.559378	0.548013	-1.87417	5.990692
	1,4,8,12	2.36340	0.26	518	0.508141	0.503337	-1.72393	6.450738

* indicates statistical significance at 10 % level

3E Robustness Test

3E.1 Financial Crisis Dummy

This section shows the figures when include the Dummy variable.

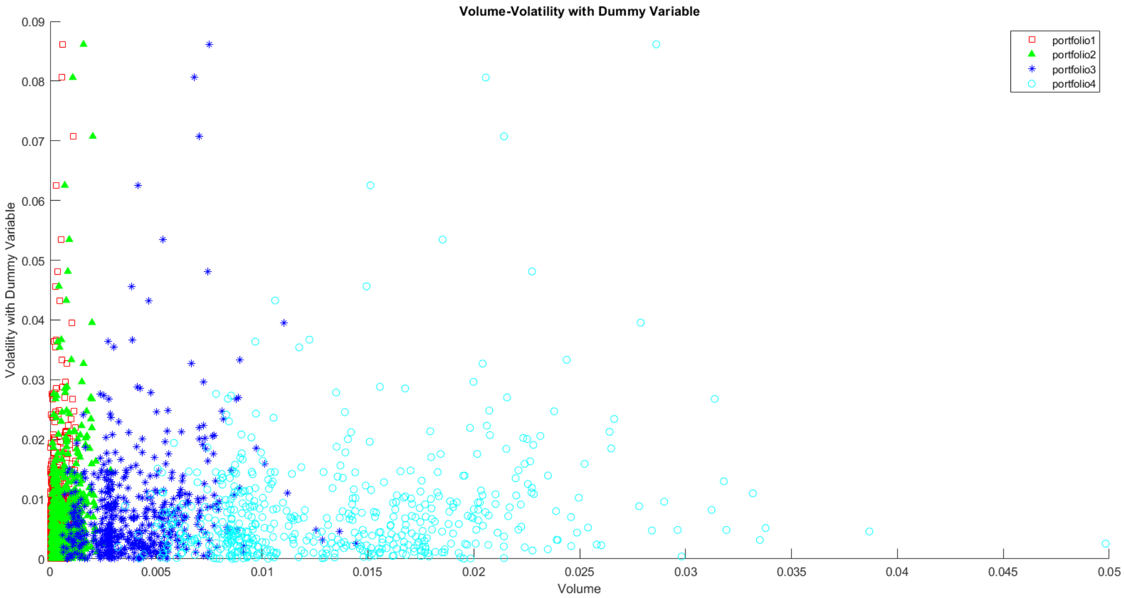
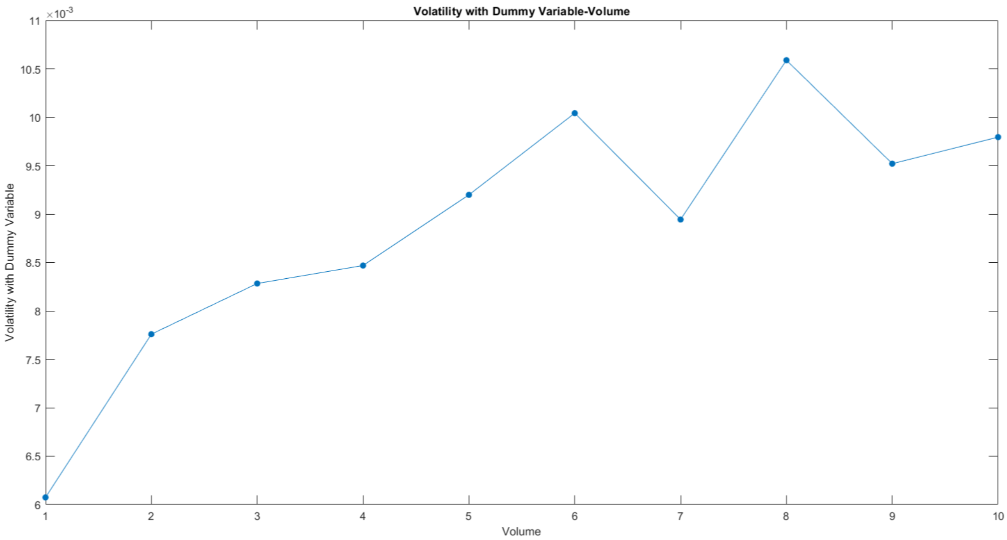


Figure 3.17: Volatility with Dummy Variable-Volume

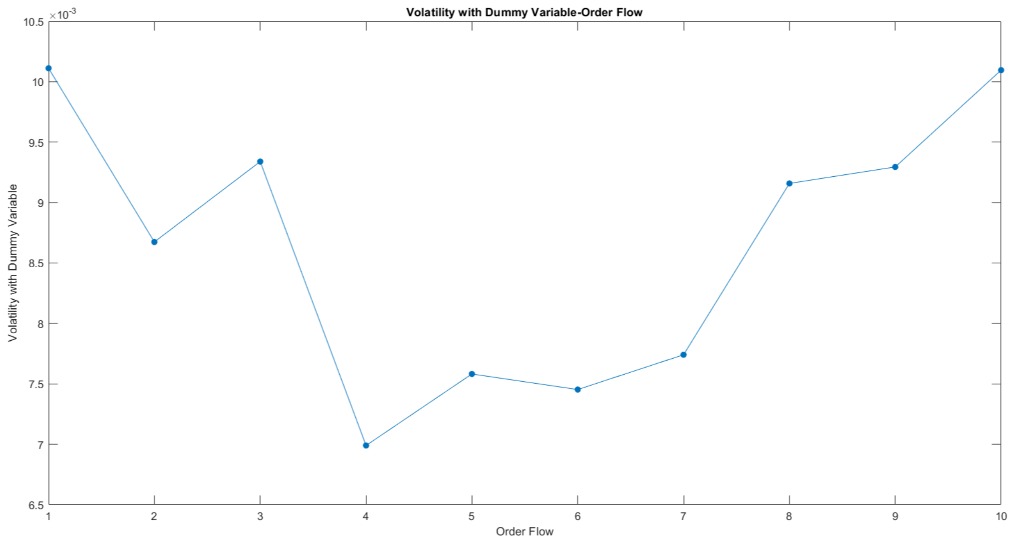
(a) Volatility with Dummy Variable-Log(Volume)



(b) Quantile Plots of Volatility with Dummy Variable-Volume

Figure 3.18: Volume and Volatility with Dummy Variable Relationship

(a) Volatility with Dummy Variable-Order Flow



(b) Quantile Plots of Volatility with Dummy Variable-Volume

Figure 3.19: Order Flow and Volatility with Dummy Variable Relationship

Table 3.24: Regression with Dummy Variable Results of Volatility/Implied Volatility-Log(Volume)

Log of Volume					
Volatility with Dummy Variable			Implied Volatility		
Portfolio	Coefficient	p-value	Portfolio	Coefficient	p-value
1	0.00133	0.13	1	-0.00140	0.66
2	0.00226*	0.02	2	0.00541	0.15
3	0.00427*	0.01	3	0.00520*	0.03
4	-0.00014	0.94	4	0.00303	0.26

* indicates statistical significance at 10 % level

Table 3.24 shows the results of volatility and log volume with a financial crisis dummy variable. These two tables use the equation below and show the results of β_i and θ_i.

Realized-volatility proxy:

$$Vol_{i,t} = \alpha_i + \sum_{j=1}^{n} \rho_{ij} Vol_{i,t-j} + \beta_i Activity_{i,t} + \varphi D_{i,t} + \eta_{it} \tag{3.42}$$

Implied volatility:

$$IV_{it} = \omega_i + \sum_{j=1}^{n} \lambda_{ij} IV_{i,t-j} + \theta_i Activity_{i,t} + \varphi D_{i,t} + \mu_{it} \tag{3.43}$$

where $Activity_{i,t}$ is log volume $logvlm_{i,t}$. $D_{i,t}$ is the dummy variable which equals 1 during the financial crisis period, otherwise equals 0. This chapter does the regression with dummy variables by using the portfolios (V1-V4 and OF1-OF4), so the i in all these equations indicates each portfolio.

Chapter 4

FX Trading Volume and Exchange Rate Predictability: Evidence from Dealer Balance Sheet Stress

Abstract:

We employ two new proprietary (OTC) FX volume and order flow datasets and provide evidence on the informative role of volume before and after 2008. Our empirical evidence suggests that US$ (spot) volume, post-2008, can become impaired when dealers' balance frictions are tighter. We focus on debt overhang costs (Myers (1977)) related to the equity holder of the bank when the dealer supplies FX dollar liquidity during shocks. We study the 2008 financial crisis and the 2020 COVID-19 shocks. Our analysis shows strong evidence that the predictability of FX volume stems from supply-side frictions and debt overhang costs.

Keywords: JEL Financial Crises(G01); Asset Pricing, Trading Volume, Bond Interest Rates(G12); International Financial Markets(G15); Foreign Exchange(F31)

4.1 Introduction

A growing body of research documents that foreign exchange (FX) trading volume contains predictive information about future currency returns. Cespa et al. (2022b) show that FX spot volume interacts with past returns to predict currency excess returns. Previous research attributes this situation to asymmetric information. Similarly, Czech et al. (2021) find that FX option volume is informative about future currency movements, with its informativeness varying across market conditions. Related studies, such as Kloks et al. (2023), observe that FX swap volume increases when dealers' balance-sheet constraints become binding. In contrast, Cenedese et al. (2021) shows that currency mispricing relative to no-arbitrage conditions is systematically related to dealer balance-sheet variables. Furthermore, Ranaldo and Santucci de Magistris (2019) links FX returns to investor behaviour driven by disagreement. Across this literature, the prevailing interpretation is that volume predictability reflects asymmetric information and demand-side learning (Campbell et al. (1993); Llorente et al. (2002)).

However, existing empirical evidence relies almost exclusively on post-2008 data or settlement platforms such as CLS Group. Recent studies still lack examination of whether FX volume predictability persists in the pre-crisis period using bilateral dealer data. This gap is critical: if predictability is fundamentally driven by asymmetric information, it should be present in any period characterised by informed trading, including the era before 2008. If it is absent, the prevailing information-based interpretation requires re-evaluation.

This paper addresses this gap using two proprietary, bilateral over-the-counter (OTC) FX datasets from two of the largest global FX dealers. We show that FX spot dollar volume predicts U.S. dollar appreciation only after 2008 and only when dealer balance-sheet constraints are tight. Before 2008, the same volume carried no predictive content; similarly, when constraints are slack in the post-crisis era, predictability vanishes. This is our central finding: the informational content of FX volume is regime-dependent, conditioned on the state of dealer balance sheets rather than being a permanent feature of the market.

Our empirical setup provides a uniquely comprehensive test. Our first dataset covers 11 currencies at a weekly frequency from 2002 to 2012, spanning nearly a decade across the Global Financial Crisis. Our second dataset provides daily volume and order flow for G9 currencies from 2018 to 2021, capturing the COVID-19 shock. Unlike the CLS settlement data used by Cespa et al. (2022b), our bilateral flow data capture customer-level volume from the dealer's own book. This distinction is important, as Cespa et al. (2022b) note that such data may contain richer and more detailed information. These datasets allow us to compare volume predictability across two distinct regimes, two independent dealers, and two major crises.

We proceed in three steps. First, we replicate and extend the analysis of Cespa et al. (2022b). We confirm that volume-return interaction coefficients are highly significant in the post-2008 sample. Our estimated coefficients are substantially larger than those reported in prior studies, suggesting that bilateral customer volumes may be more informative than settlement-based aggregates. We also find that volume is consistently significant in our sample, in contrast to the model in Cespa et al. (2022b).

Second, we document a structural break: this predictability disappears entirely in the pre-2008 period. This result suggests that the drivers of FX volume predictability are specific to the post-crisis environment rather than a fixed characteristic of foreign exchange markets.

Third, we investigate the conditioning variables for this predictability. The post-crisis era saw a structural increase in funding costs for dealer banks, driven by regulatory changes (e.g., the Dodd-Frank Act) and elevated credit spreads (Berndt et al. (2024)). These costs create balance-sheet frictions (debt overhang)(Myers (1977); Andersen et al. (2019); Cerrato and Mei (2025)). We proxy for balance-sheet constraints using three measures: the average 5-year CDS spread of the 12 largest dealer banks (Andersen et al. (2019); Burnside and Cerrato (2025b)), intermediary leverage (He et al. (2017)), and the LIBOR-OIS spread (Cooperman et al. (2025)). Sorting the sample by the median of each proxy, we find a consistent pattern: FX volume predicts dollar returns only during high-constraint periods.

These findings challenge the prevailing focus on asymmetric information. If informed trading were the primary driver, predictability should be shown throughout our sample. Instead, predictability arises only when frictions are high, suggesting that debt overhang is also an important proxy for affecting the volume predictability of price. While we do not rule out asymmetric information as a complementary channel, it cannot fully account for this regime-dependent evidence.

Our findings have significant implications for both academic research and market practice. For the FX literature, our results suggest that the informational content of trading volume is not a structural market invariant. Instead, it is a regime-dependent outcome tied to an increase in dealer balance-sheet costs. The economic environment in which volume is generated is as critical as the volume itself.

For risk management and investment, our results imply that the predictive power of FX volume should not be extended to periods of low balance-sheet stress. Monitoring dealer constraints through CDS spreads, leverage, or funding spreads is essential for determining when volume signals are likely to be informative.

In sum, this paper establishes that the predictive content of FX volume is conditional. Dealer balance-sheet frictions are the key conditioning variable, a result that holds across two major crises and two independent global dealers.

4.2 Data and Summary Statistics

Summary statistics of the data.

4.2.1 *Forex Volume*

We use two confidential (bilateral) datasets from two large FX dealers. The first dataset uses 11 currencies against the US dollar (USD). The currencies include Euro(EUR), Japanese yen (JPY), British pound (GBP), Swiss franc (CHF), Australian dollar (AUD), New Zealand dollar (NZD), Canadian dollar (CAD), Mexican peso (MXN), South African rand (ZAR), Singapore dollar (SGD), Hong Kong dollar (HKD). This dataset contains only seven G10 currencies (EUR, JPY, GBP, CHF, AUD, NZD, and CAD). For each currency pair, we have FX US$ trading volume for almost twelve years (2001-2012) at a weekly frequency. Data is reported in Table 4.1 (A). We also have matching order flows for the same currencies, which have been kindly provided by Burnside et al. (2025a).

The second dataset consists of daily US$ equivalent volume across the G9 currencies. We have volume data for the Australian dollar (AUD), Canadian dollar (CAD), Euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), British Pound (GBP), Swedish krona (SEK), and Swiss franc (CHF). This measures the average daily volume based on client trades over the last 20 days normalized by the 6-month median volume of those trades. The volume indicators are based on the total buy and sell trades of a currency by client type and are aggregated in USD equivalent terms regardless of the cross in which they are transacted. These are calculated separately for hedge funds, asset managers and other clients. A value greater than one indicates a median volume higher in the last 6 months. The data spans the period 2014 to 2023 at a daily frequency, although in this paper, we only focus on the period 2018 to 2021 and the COVID-19 period. Data is reported in Table 4.1 (B). We also have, for the same dealer, order flows for the same currencies spanning the same period.

For our first dealer, the sample consists of 493 observations for each currency from the first week of November 2002 to the fourth week of March 2012. Trading volume is expressed in billion US$. Table 4.1 (Panel A) shows the average weekly volume for our currencies. The Euro is the currency with the largest volume, while the Hong Kong dollar is the currency with the smallest weekly volume. It is worth noting that low-interest-rate currencies are, in general, the ones with the largest volume, much larger than high-interest-rate currencies. For a description of the statistics of order flow data from the first dealer, refer to Burnside et al. (2025a).

Table 4.1 (Panel B) shows the volume data of the second dealer. As we mentioned, this is an index which relates to the volume of US$ equivalent trades, spanning Jan 2018 to Dec 2021. Trading volume is expressed relative to the median volume. The average is slightly above 1, suggesting increasing volume over time. Both investor categories have a positive skew - i.e. higher volume periods are more common.

Table 4.2 reports aggregate and disaggregated order flow from the second dealer over the 2018-2021 period. Order flow is defined as net buying minus selling, with positive values indicating purchases of foreign currency (sales of USD). All figures are normalised by recent median trading volumes. Over the full sample, aggregate clients are net sellers of EUR and AUD and net buyers of CHF and GBP. Financial clients are small net buyers for most currencies, while non-financial clients, predominantly corporates, are net sellers of all currencies except CHF.

4.2.2 *The Empirical Model*

We use the weekly spot exchange rate from WM/Refinitiv (via Datastream). WM/Refinitiv weekly exchange rates are simultaneously recorded on Friday at 4 pm in London. We calculate the weekly exchange rate return as the log difference between the spot exchange rate:

$$\Delta s_{i,t} = s_{i,t} - s_{i,t-1} \tag{4.1}$$

where $\Delta s_{i,t}$is the exchange rates log return of each currency pair $i$at time t. And $s_{i,t}$is the log of the exchange rate price of currency pair i at time t.

We then compute the excess return for each currency pair:

$$r_{i,t} = \Delta s_{i,t} - (ir^{i}_{i,t-1} - ir^{\$}_{i,t-1}) \tag{4.2}$$

Where $r_{i,t}$ is the excess return for each currency i, $ir^{\$}_{i,t-1}$ is the short-term interest rate of USD and the $ir^{i}_{i,t-1}$ is the short-term interest rate of quoted currency i at observed time $t-1$. We replace short-term interest rates with forward rates under the assumption that $(ir^{i}_{i,t-1} - ir^{\$}_{i,t-1} \approx f_{i,t-1} - s_{i,t-1})$, and express the excess return as:

$$r_{i,t} = \Delta s_{i,t} - (ir^{i}_{i,t-1} - ir^{\$}_{i,t-1}) = (s_{i,t} - s_{i,t-1}) - (f_{i,t-1} - s_{i,t-1}) = s_{i,t} - f_{i,t-1} \tag{4.3}$$

where $f_{i,t-1}$ is the log of 3 month forward rate of currency i at time $t-1$. To be able to use all our currencies, we use the 3-month forward rate of all currencies from Barclays Bank PLC (via Datastream), as shorter maturities are not available for non-G7 currencies. However, for robustness, in the Appendix (4C), we also show the results when using the one-month and one-week maturities. Note that we use excess returns only in the first part of the paper to be consistent with Cespa et al. (2022b), but we could use returns, as we do in the second part of the paper, given that our main focus is to study the information of the FX volume and not exploiting this for FX trading.

4.3 Does FX Volume Contain Information?

We begin by documenting the empirical patterns emphasised in the FX-volume literature, which interprets volume predictability as evidence of information asymmetry. Our goal in this section is diagnostic: to establish when these patterns arise, not to adopt their interpretation. Does FX volume contain information? What sort of information does it contain? This has been investigated in some recent and important papers, Czech et al. (2021), Kloks et al. (2023) and Cespa et al. (2022b). Cespa et al. (2022b), for example, use data on FX spot volume and focus on asymmetric information driving the FX volume. This is a plausible explanation. For example, if FX volume moves with FX volatility, then one can assume that higher volatility increases the demand for dollar liquidity, and this affects the FX volume and the dollar exchange rate. Therefore, one would observe a predictive power of the volume on returns (or excess returns). In this context, demand-based models resting on asymmetric information could provide a possible explanation (for example, as in Cespa et al. (2022b)). However, those models do not consider the possibility that the supply of dollars can also contribute to the predictability of the volume. We shall discuss this in greater detail in the next sections.

Furthermore, the data used in that literature, including Cespa et al. (2022b), originate in a settlement-specific platform, CLS Group. In this paper, we use bilateral flow data. This is important as the two sources of FX data are structurally very different. Therefore, to corroborate the results of Cespa et al. (2022b), as a first step, we redo their analysis using our data sets. Crucially, we divide our sample into two parts, before and after 2008. We shall discuss the reason in the next section. As in Cespa et al. (2022b), we also control for GARCH volatility, bid-ask spread and more.

For the bid-ask spread, we collect the bid and ask prices from Refinitiv (via Datastream). The larger the bid-ask spread, the larger the FX illiquidity[1] To mitigate heteroskedasticity and trends in the time series of volume, we follow Cespa et al. (2022b) and calculate the normalized volume as:

$$nv_{i,t} = log(vlm_{i,t}) - log(\frac{\sum_{s=1}^{N} vlm_{i,t-s}}{N}) \tag{4.4}$$

where $nv_{i,t}$ is the normalized volume, $vlm_{i,t}$is the original volume. We set N equals 12.

$$r_t = A + Br_{t-1} + C(r_{t-1} \times nv_{t-1}) + Dnv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.5}$$

where $x_{i,t-1}$ controls for currency-pair-specific measures of liquidity and volatility. The coefficients A and ϕ denote currency pair and time fixed-effects. In this model, we add the $(r_{i,t-1} \times nv_{i,t-1})$ interaction term.

4.4 Preliminary Results

This section documents descriptive patterns in FX volume and order flow that motivate our investigation of the role of dealer balance-sheet frictions in FX volume predictability. Table 4.3 shows the results. We include time and currency fixed effects and use double-clustered standard errors.

In columns 1-3, we use all 11 currencies. We focus on the interaction coefficient, which, following the model in Cespa et al. (2022b), we expect to be highly significant.

In columns 2 and 3, the interaction coefficient is indeed highly significant. Based on similar results, Cespa et al. (2022b) conclude that asymmetric information in the FX market is relevant and that FX trading volume is informative. Our results confirm

[1] Bid-ask spread is also a measure of asymmetric information. (Ranaldo and de Magistris (2022)) Larger bid-ask spreads are proxies for larger asymmetric information.

it.[2]

Table 4.3 already shows some novel and interesting differences with respect to what is reported in the literature. For example, our estimated interaction coefficients are much larger than the ones reported in many recent papers, including Cespa et al. (2022b). This may suggest that customers' volumes are more informative than the ones used in most papers (Cespa et al. (2022b) and Czech et al. (2021) make a similar remark).

More importantly, the degree of persistence in currency returns that we document is surprisingly higher, given that we use weekly data. Finally, and very importantly, volume on its own is always highly significant, while in most recent FX empirical papers (and in the model in Cespa et al. (2022b)), volume on its own is insignificant.

In columns 4-9, we control for large and small volume, bid-ask spread and volatility. We divide groups into high (low) bid-ask spread, volume and volatility based on the median. Overall, the results are reasonably consistent with Cespa et al. (2022b), and one could interpret this evidence as supportive of asymmetric information.[3]

Given that our data set also spans a long period before the 2008 financial crisis, and it is the only FX volume covering such a long time span, we now focus on that period. If FX volume has some predictive power, this should also be the case before 2008.

Table 4.4 shows the results. There is no evidence of the predictability of the FX volume before 2008. This result also contrasts with the FX microstructure literature, suggesting an informational role for the order flow unless volume and order flow capture different types of information.[4]

The empirical evidence in Table 4.3 and Table 4.4 suggests that while FX volume can predict currency returns during the post-2008 period, it fails during the period before 2008. We conjecture that this difference is related to the structural increase in dealer balance-sheet costs after 2008, which we investigate below.

[2] We have also used daily volume data for the second dealer and the period 2018-2021, confirming that the interaction coefficient is also highly significant. Results are, in general, supportive of the Cespa et al. (2022b) argument. See Appendix 4E

[3] Results in Table 4.3 are robust to different measures of volatility. See Appendix

[4] Cespa et al. (2022b) suggest that the informational role of volume and order flow is different.

A recent paper (Huang et al. (2025)) suggests that the supply curve for FX liquidity is steeper between 2014 and 2022. The paper proposes two liquidity cost measures based on the triangular no-arbitrage condition and controlling for FX volume to show that in times when the dealer is constrained (VaR reaches risk limits or funding costs are higher), the relationship between FX volume and cost of providing liquidity becomes weaker. The important difference between this paper and ours is that, first, we do not rely on CLS data but on OTC bilateral volumes from two of the largest FX dealers. Second, we cover a much longer period that spans before and after 2008, and the main objective of our study is not to conduct a systematic analysis of the FX liquidity but rather to study the predictability content of the FX dollar volume.

4.4.1 *Debt Overhang in FX Markets*

In this section we focus on debt overhang and explain how it relates to FX dealers trading bilaterally with clients. We use debt overhang in the Myers marginal-incentive sense. As we shall discuss in this section, the periods we study in this paper are periods where the equity of the banks was already low, and debt overhang was high.

There is strong evidence (Lu et al. (2023)) that dealers' desks use internal capital markets, especially in times of shocks, to search for the necessary liquidity to meet clients' demands. However, given the stiffness of (internal and external) capital at times of market turmoil, dealers will try to run a matching book with clients as much as possible as a way to reduce the consumption of capital.[5]

Suppose that following an exogenous shock, the equity capital of the dealer falls and, at the same time, the demand for US$ from clients surges (additional demand). To accommodate the demand, dealers will need to commit their own capital. However, generally, they are reluctant to do so to support the liquidity, particularly when their capital is already low. For example, for the Treasury market, Duffie et al. (2023) show that dealers post large bids and ask prices to recover these costs or as a way of not being hit by customer flows. Adrian et al. (2017) makes a similar case but relates it to

[5] Generally, dealers' desks are allocated capital daily, and it is very expensive to borrow extra capital from the treasury or even externally.

higher regulatory capital after 2008.

This situation introduces debt overhang costs. This is also consistent with Ferreira et al. (2024), who show that when USD liquidity is limited, the central bank conducts USD sale operations anticipating stronger spot price effects. The intervention in the FX market by the central bank has a stronger impact when FX dealers face tighter financial conditions.

The empirical results in recent papers (for example, Huang et al. (2025)) are also consistent with this, although those papers do not focus on or study this novel mechanism based on shareholders' incentives.

Note that in this paper, we use the term debt overhang broadly to capture the idea that, when equity is scarce, dealers face an elevated shadow cost of balance-sheet expansion, even absent binding regulatory constraints. Therefore ours is a capital structure friction rather than a binding constraint as in the literature. In the empirical analysis, we shall distinguish this mechanism from generic funding stress by exploiting variation in dealer CDS spreads and the timing of balance-sheet shocks.

4.4.2 *Motivating Evidence*

Is debt overhang relevant during the period we study in this paper? In this section, we present and discuss evidence in support of debt overhang. In Figure 4.1, we plot the intermediary leverage from He et al. (2017), at a monthly frequency over the period 2002 to 2012 (Panel a) and 2018-2021 (Panel b). These are the two periods we study in this paper. The leverage is the ratio of total debt to market equity. This measure of leverage is directly linked to the dealer's equity capital and, therefore, to debt overhang (see discussion in the previous sections).

Intermediary leverage as a proxy for intermediaries' financial frictions is also supported empirically and theoretically in Adrian et al. (2015), He et al. (2017), only to cite a few. Larger leverage corresponds to times when equity capital is lower, and, therefore, the marginal utility of the wealth of the dealer is higher (balance sheet constraints following debt overhang). See also the discussion in Burnside et al. (2025a) and He et al. (2017). According to He et al. (2017), primary dealers' leverage expands in states when equity is declining, and it increases in states when the intermediary equity is increasing.

In Panel (a), the red vertical bar is the start of our empirical analysis (i.e. the end of 2007), while the green bar corresponds to the middle of 2009 to capture the effect of the Dodd-Frank Act, which was proposed and discussed in 2009 and signed in 2010. For Panel (b), the vertical bar corresponds to the start of the COVID-19 shock (March 2020).

Figure 4.1 (Panel a) is suggestive, at least for two reasons: first, intermediaries' leverage peaked in 2009 when the Dodd-Frank Act started to be discussed, but not during the 2007-2008 financial crisis. Leverage started to decline sharply in late 2009. The discussion of the Dodd-Frank Act coincides with a significant deleveraging.

The leverage adjustment in 2009 is consistent, amongst other things, with dealers starting to be concerned with the effect of the Dodd-Frank Act and the extra costs on their balance sheets and being more cautious about balance sheet usage.[6] Figure 4.1 is consistent with a scenario where debt overhang to the dealers increased sharply in 2008 and early 2009 and fell in late 2009, remaining sticky after that period.

We now turn to the COVID-19 shock. In Panel B, we plot the dealers' leverage before and after the COVID-19 shock in 2020. We observe a very similar picture. Leverage peaked sharply during the COVID-19 period and reverted back to previous levels only in 2021. As before, the large increase (decrease) in leverage is consistent with a situation where dealers are largely constrained, and debt overhang is relevant.

Andersen et al. (2019) discuss debt overhang costs related to funding costs and funding value adjustment (FVA), for the swap market. They show that dealers' FVA can be viewed as wealth transfers from equity holders to creditors (i.e. debt overhang). This cost can be proxied by the dealer's credit spread. Cerrato and Mei (2025) use a balance sheet model to motivate it.

Burnside and Cerrato (2025b) proxy debt overhang cost related to FVA when studying Covered Interest Rate Parity (CIP), using the 5-year CDS spreads of the 12 largest dealer banks.[7]

[6] Leverage may also be affected by the equity injection in banks starting in 2009.

[7] The CDS is an index containing an equal-weighted average of the largest 12 US and European

To dive deeper into our discussion above, we follow Burnside and Cerrato (2025b)), and Cerrato and Mei (2025), and use the CDS spread of large US and European dealers to proxy for debt overhang arising from higher funding costs. We complement our results by using market measures like the 3-month Libor minus the OIS spread. Figure 4.2 plots the average cross-sectional CDS spread of the largest six US and six European banks, as well as the three-month LIBOR minus OIS spread, as an alternative market-based proxy.

The picture emerging from Figure 4.2 is consistent with Figure 4.1. Debt overhang cost stemming from funding costs is significantly higher during the period we study in this paper. It was very small before 2008, but it has increased sharply starting from 2008, and again in 2009 and has remained higher since then. As documented in Burnside and Cerrato (2025b), and Andersen et al. (2019), the increase in dealers' debt overhang has had a significant impact on arbitraging Covered Interest Rate Parity (CIP) deviations. Taking Figure 4.1 and Figure 4.2 together, we can reasonably conjecture that debt overhang was significantly higher during the period we studied in this paper.

Since we have granular data on the FX volume for the first dealer, we dive deeper into the balance sheet and in Figure 4.3 and Figure 4.4, we plot the (monthly) FX volume and the volatility of the FX volume over the sample period. FX volume increased consistently between 2003 and 2008. The dealer supplies dollar liquidity at any given level of dollar demand. This suggests that (unconstrained) dealers were able to accommodate the dollar demand with only a modest impact on dollar liquidity and the exchange rate. However, the volume has fluctuated around its mean between 2009 and 2012. After the 2008 financial crisis, we observe large swings in FX liquidity intermediation. This large fluctuation of the FX volume is consistent with higher balance sheets' frictions constraining the supply of dollars post-2008.

In Figure 4.4, we plot the (monthly) volume volatility over the same period. Volatility increased sharply in 2008 and decreased thereafter, but it has never gone

Dealers. This index is highly liquid and difficult to manipulate by a single dealer. The index reflects funding costs for receivable derivatives that the dealer charges to clients to provide liquidity in the OTC market.

back to the 2003-2008 level. This higher volatility is also consistent with significant balance sheet frictions. For example, Kottimukkalur (2019) makes this case to explain the presence of arbitrage opportunities due to supply-side constraints.

Figure 4.5 shows (the cross-sectional average) the bid-ask spread of our currencies (median quarterly). Bid-ask prices fell until the end of 2007 and then started to increase. The dynamics in the bid-ask spread in Figure 4.5 are also consistent with higher balance sheet frictions. As explained by Andersen et al. (2019) and Cerrato and Mei (2025), in the presence of debt overhang, dealers will need to extract some "donations" from the clients to compensate equity holders. In the OTC market, this donation takes the form of larger spreads.

Finally, in Figure 4.6, we computed the median, within each quarter, of the aggregate US$ FX volume relative to the dealers' total assets in that quarter. The trend we observe is also consistent, amongst other things, with balance sheet frictions, and it suggests that after 2008, there is less space on the dealer's balance sheet for any additional unit of FX spot intermediation.

The evidence in this section would suggest that debt overhang has been persistent during the period we study in this paper, and it could be a plausible explanation for the dynamics observed in our data. We conjecture that this supply-side friction can help us to rationalise the different results we report in Table 4.3 and Table 4.4 and understand why FX volumes (post-2008) contain predictive information. In the next section, we test this conjecture formally.

4.4.3 *Debt Overhang and FX Volume*

We start with a simple panel regression where we regress changes in fx volume on changes in CDS spreads. The idea is, in part, motivated by Kloks et al. (2023), who find, for the FX swap market, that volume increases in times when dealers' balance sheet constraints bite, but they cannot fully explain why. We suggest that larger fx volumes are consistent with dealers' scrambling for dollars following shocks on equity capital. We study whether changes in dealers' CDS spread (a proxy for debt overhang costs) can predict changes in fx volume. Of course, this does not establish a causal relation, but it helps us to understand if FX volume may be associated with information about dealers' balance sheet costs (in our specific case, debt overhang costs).

We report the results in Table 4.5. We find strong evidence that changes in CDS spread are associated with changes in fx volumes next period. This association is positive, which implies that when debt overhang cost increases, fx volume also increases.

Furthermore, we do the simple panel regressions using (weekly) data between the end of 2007 and 2012 (first dealer). These regressions will be useful to set a baseline benchmark. We use the same empirical model as before, but focusing on the lagged volume coefficient as opposed to the Cespa et al. (2022b), whose focus is mainly on the interaction coefficient to motivate asymmetric information. We study the predictability content of the FX volume on dollar returns.

The lagged volume used will also help us to mitigate endogeneity while focusing on the predictability of the FX volume. We control the demand for US dollars. We employ a set of fixed effects and control for variables which generally correlate with the demand for US dollars (see discussion in the previous section). We focus on returns instead of excess returns as in Cespa et al. (2022b).[8]

The bank's CDS spread is a direct and relevant proxy measure of debt overhang cost arising from debt (equity) financing (see also Andersen et al. (2019) and Cerrato and Mei (2025)). We complement it by using a market-based proxy, that is, the Libor-OIS spread (Cooperman et al. (2025)). When the spread is larger, the debt overhang cost for the dealer increases. We also include leverage for the reasons explained earlier.

In Table 4.7, we sort the data using the median of CDS (Leverage, LIBOR-OIS) and form two groups: larger (smaller) CDS spreads (leverage). We associate this with a higher (lower) debt overhang cost for the dealer. We then regress returns on lagged returns and lagged FX volume. We use robust standard errors, and the same econometric design as well as the controls we have used in Table 4.3 and Table 4.4.

We note that lagged FX volumes are all significant when the debt overhang cost

[8] While the focus in Cespa et al. (2022b) is on the interaction coefficient term as their model suggests that asymmetric information directly affects it, and they employ FX trading strategies, the focus of our paper is on the predictability of FX volume and dealers' balance sheet frictions. Therefore, the interaction coefficient does not play any role in our model. However, our appendix shows the results when using excess returns and the interaction coefficient, and they are in line with what is already reported in Table 4.7.

bites, while they are insignificant otherwise. Finally, large FX dollar volume is associated with large US$ returns (i.e. US$ appreciation). The dollar FX volume does contain predictive information, but only conditionally to a higher debt overhang. This suggests that the predictive content of the FX volume stems from the supply side. Recently, Huang et al. (2025) made a similar case for the FX spot liquidity. Our results are in line with theirs. They are also in line with Kloks et al. (2023), although that paper focuses mainly on the effect of dealers' constraints on the FX swap market, while we focus on the spot market and the predictability information of the FX spot volume. Finally, we report in column 7 that unconditional estimates of the beta coefficient and volume are insignificant, and the coefficient is much smaller in size than the conditional ones.

In Table 4.8, we report results using the first dealer FX volume (weekly) and the period before 2008. Clearly, debt overhang cost was not an issue during that period, and indeed, the evidence is much weaker over that period.

In Table 4.10, we use the dealers' CDS spreads to form percentiles based on smaller CDS spreads (least constrained dealers) and larger CDS spreads (most constrained). Conditionally to the CDS's spread size, we estimate the (interaction coefficient) beta in Cespa et al. (2022b). In light of the discussion above, we conjecture that larger and more significant betas are associated with higher balance sheet frictions for the dealer. Lagged volumes are significant regardless of how we measure balance sheet constraints. These results also suggest that fx volumes are associated with US$ appreciation in bad times. The interaction coefficient is significant in general, but much bigger in size when the dealer's balance sheet usage cost is the highest (i.e. in bad times).

The size of the beta coefficients is highly significant and larger when balance sheet constraints tighten. For example, the size of the beta coefficient when the debt overhang cost is higher (conditional beta), is larger than the unconditional one. In fact, the former is larger and highly significant. This empirical evidence suggests that the interaction beta in Cespa et al. (2022b) is also consistent with the persistent effect of debt overhang costs on FX returns (or at least correlated with it).

While the empirical evidence in this section sheds new light on Kloks et al. (2023), suggesting that higher fx volume is associated with fx illiquidity and the flight to safety (see also Cenedese et al. (2021)), given that the leverage ratio requirement (LRR) was not binding over the sample period we studied so far, our results cannot be related to regulatory frictions. This would also imply that LRR cannot be the only explanation for what was observed in Kloks et al. (2023), as it is likely that other and more persistent (i.e. not just quarter-end effects) forces are at work.

To further control for demand-side shocks, in Appendix 4F, we also control for the dealer order flow. We do not show the estimated coefficient on the order flow, but they are all statistically insignificant. The overall results stay unchanged.

The results in this section suggest that dollar volume can predict dollar returns but only when debt overhang is significant. This evidence supports our conjecture that the predictive content of FX volume is driven by balance-sheet frictions rather than being a permanent feature of the market.

Our results add further evidence to the literature on the financial channel for US dollar appreciation, with the critical difference that we focus on primary G-SIBs dealers (Bruno and Shin (2015), Jiang et al. (2021), Kekre and Lenel (2024)).[9]

Given that the intermediaries in this paper are also the largest players in the interdealer market, our results might suggest that, in periods of negative shocks, the FX flows in customer and interdealer markets are correlated, increasing substantially the liquidity costs in both markets. We leave this topic for future research. Our findings do not exclude asymmetric information as a complementary channel, but they suggest that supply-side frictions related to dealer balance sheets play a first-order role in generating the predictability of FX volume.

4.5 The COVID-19 Shock

In this section, we turn to the fx volume provided to us by our second dealer. We study the sample period 2018 to 2021 and the COVID-19 shock.

[9] Note that a large part of the US$ liquidity, which is the focus of the financial channel argument of exchange rates, is intermediated by a few large dealers and these can be viewed as marginal price setters. This is indeed the case for the spot market (Krohn and Sushko (2022)).

To study the relevance of debt overhang cost on FX spot intermediation over our sample period, we do a simple regression between the change in volume and the change in CDS, similar to Table 4.5. We show the results in Table 4.6. Table 4.6, Column (1) shows the results for leverage investors, while Column (2) shows the results for Real Money. The results in Table 4.6 are overall consistent with the ones reported earlier.

Furthermore, as before, we divide the sample into two bins, higher and lower balance sheet frictions as proxied by the dealers' 5-year CDS spread, LIBOR-OIS spread and also Leverage, according to their median value. We do a similar analysis as before. Table 4.9, Panel A shows the results for leveraged investors, while Panel B shows the results for Real Money, and Panel C shows the total of the two. Note that volume data from the second dealer is calculated as the average daily volume over the past 20 days, normalised by the 6-month median volume of a currency and investor client type. A value greater than one (1) means that more recent daily volume is above its longer-term median, and less than one, means the opposite.

The results in Table 4.9[10] are in line with the ones reported earlier. Although coefficients are generally significant in both cases of higher (lower) debt overhang costs, the estimated coefficients in the former scenario are larger, and the R-squared in the case of lower debt overhang costs is negative. In sum, larger FX volumes can predict US dollar appreciation but only conditionally to higher debt overhang cost (i.e. higher balance sheet frictions).

4.6 Conclusion

We provide evidence that FX spot dollar volume can predict subsequent dollar appreciation, but only conditionally to the severity of dealer balance-sheet frictions. Using two proprietary bilateral FX datasets from two of the largest global dealers, spanning a long period before and after 2008, we document that this predictability is entirely a post-2008 phenomenon. Before 2008, FX volume contained no predictive

[10] In April 2020, the U.S. FED implemented a very large asset program purchase (QE) in response to the financial market turmoil following the COVID. Appendix 4B shows the same results when the period of the FED intervention has been dropped. As we can see, we obtain even stronger results in this case

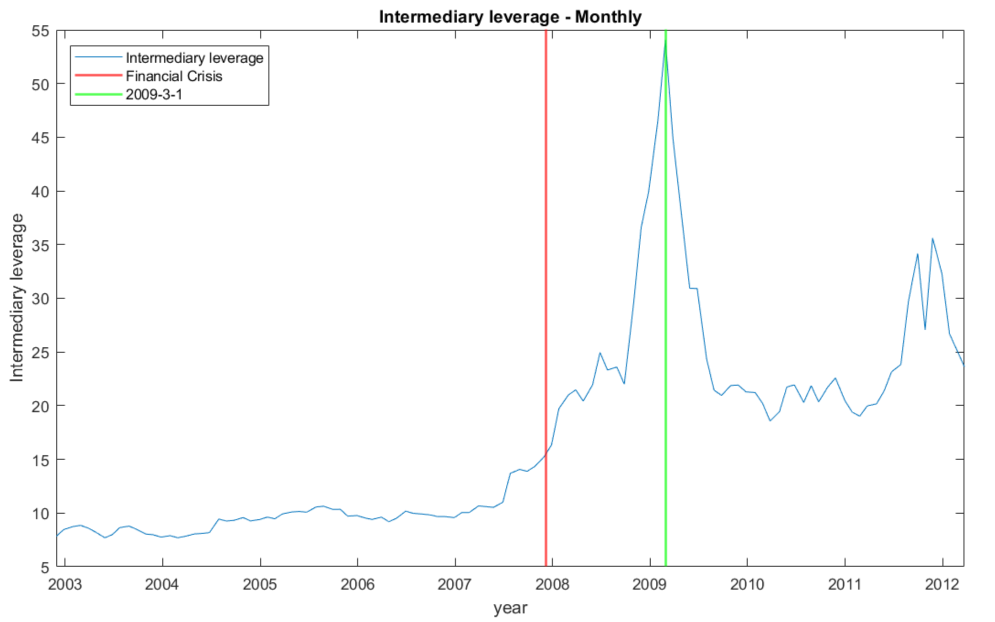
information about exchange rate movements.

Our results are robust across three proxies for balance-sheet stress, which are dealer CDS spreads, intermediary leverage, and the LIBOR-OIS spread. Our results hold for two dealers and across two distinct crisis episodes (the 2008 Global Financial Crisis and the 2020 COVID-19 shock). We do not fully exclude leverage ratio requirements (LRR) as an additional explanation, but we point out that LRR is only the tip of the iceberg, as additional and more persistent forces may be at work. Similarly, our findings do not exclude asymmetric information as a complementary channel, but they suggest that supply-side frictions related to dealer balance sheets play a first-order role.

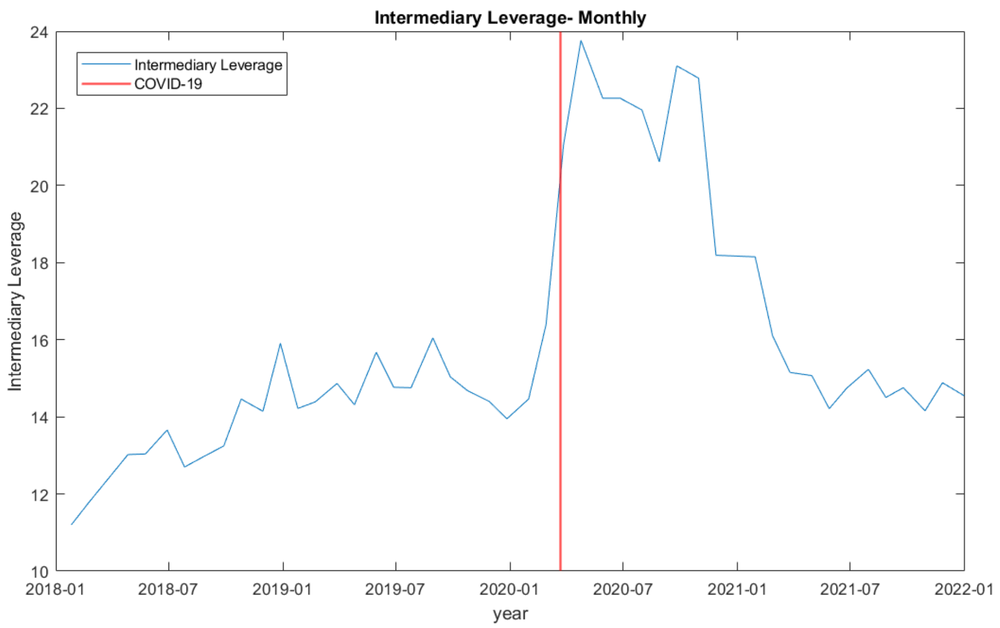
These results have implications for the broader FX literature. They suggest that the informational content of FX volume documented in recent studies is not a timeless feature of the market but a regime-dependent outcome shaped by the post-2008 increase in dealer balance-sheet costs.

Figure 4.1: Intermediary Leverage

(a) Intermediary Leverage - Monthly for Financial Crisis



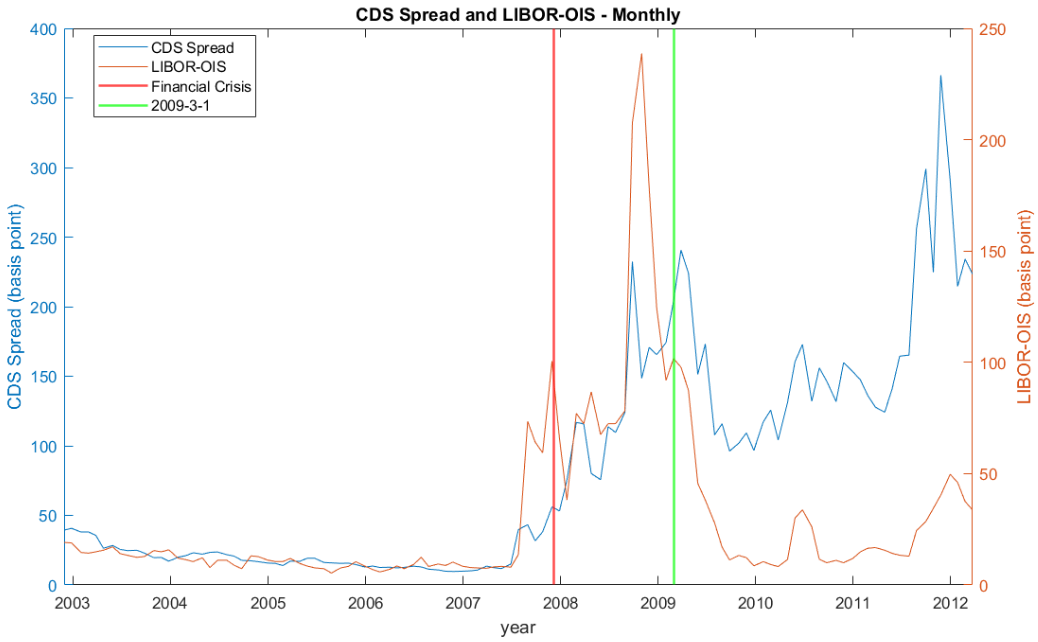
(b) Intermediary Leverage - Monthly for Covid-19



In Figure 4.1, we plot the intermediary leverage from He et al (2017), at a monthly frequency over the period 2002 to 2012 (Panel a) and 2018-2021 (Panel b).

Figure 4.2: CDS Spread and LIBOR-OIS

(a) CDS Spread and LIBOR-OIS - Monthly for Financial Crisis



(b) CDS Spread and LIBOR-OIS - Monthly for Covid-19

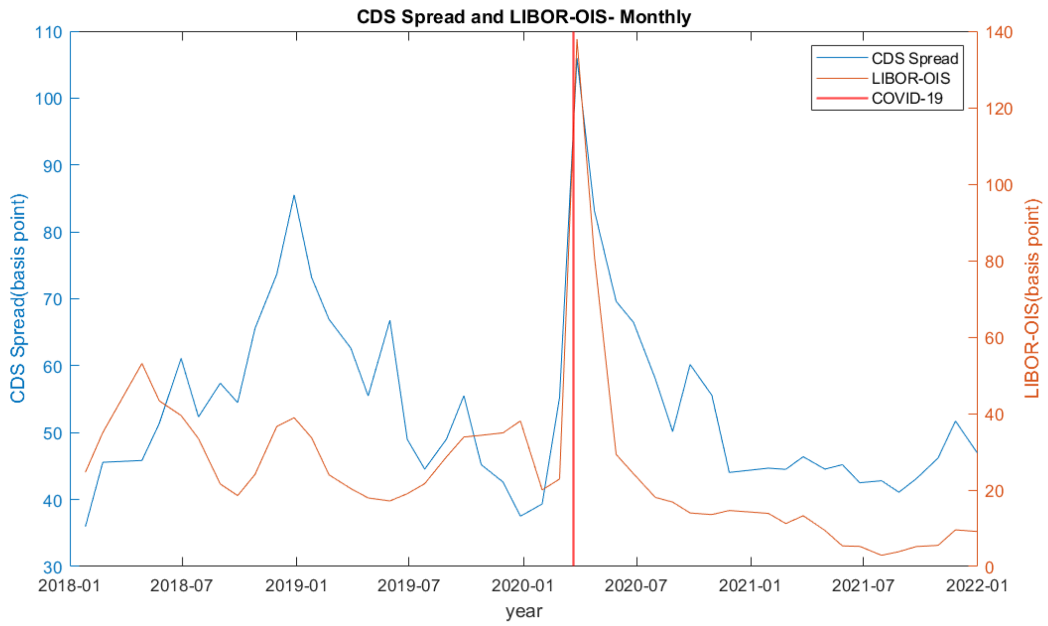
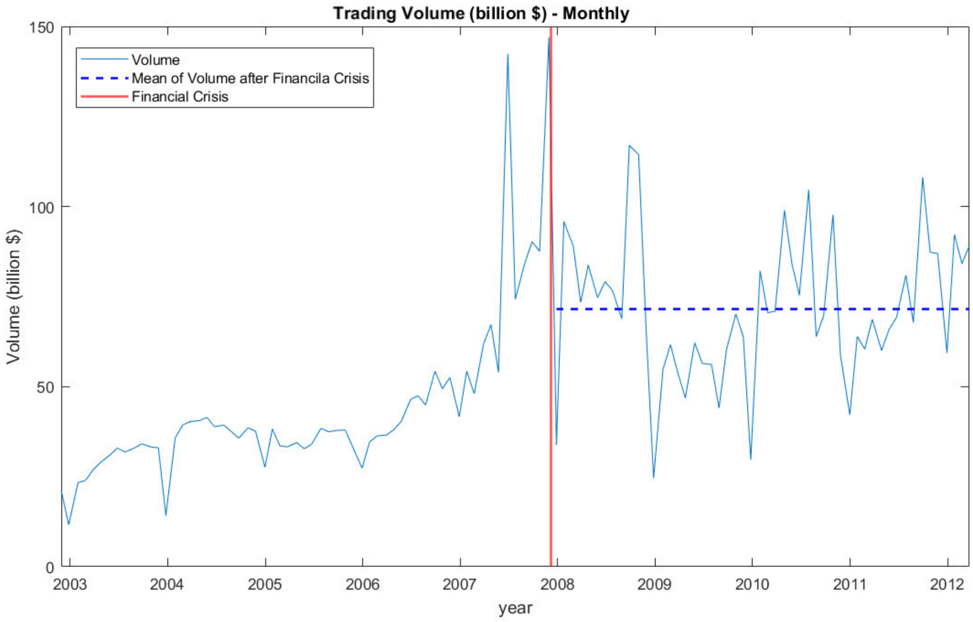


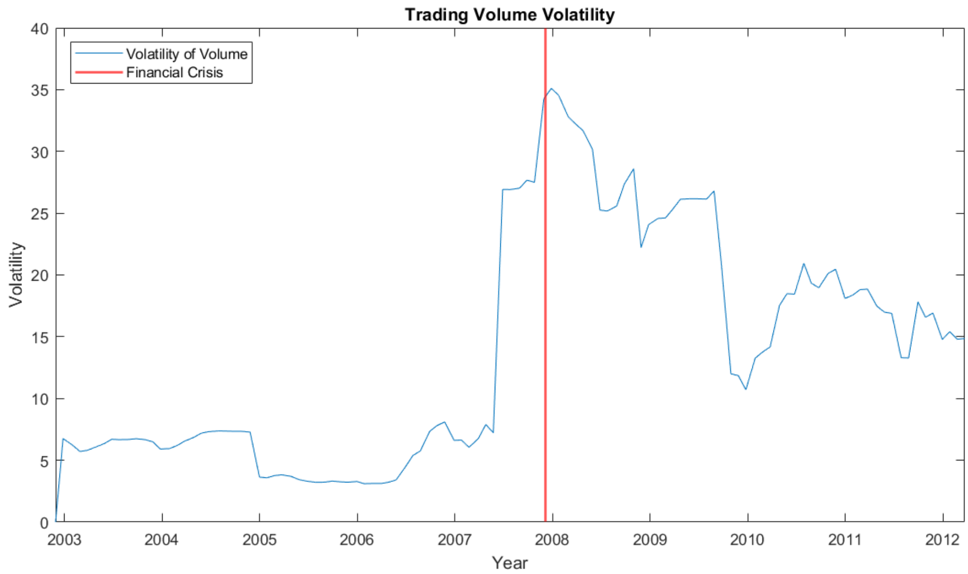
Figure 4.2 plots the average cross-sectional CDS spread of the largest six US and six European banks, as well as the three-month LIBOR minus OIS spread, as an alternative market-based proxy.

Figure 4.3: Volume



In Figure 4.3, we plot the trading volume data by using the first dealer's data which uses the sample from 2003 to 2012.

Figure 4.4: Volatility of Volume



In Figure 4.4, we show the volatility of trading volume.

Figure 4.5: Bid-Ask Spread

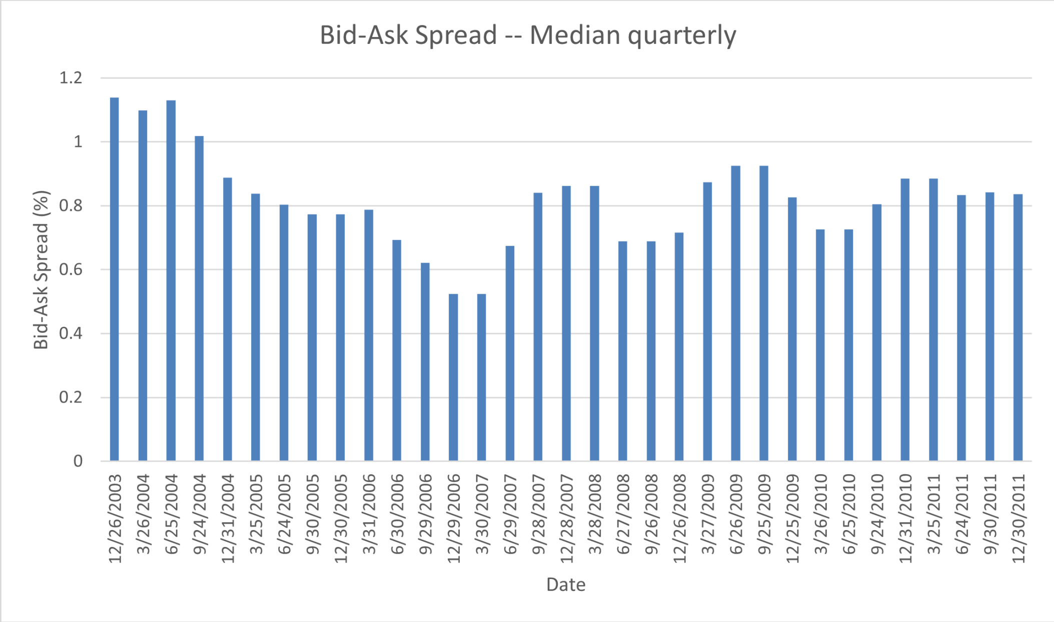
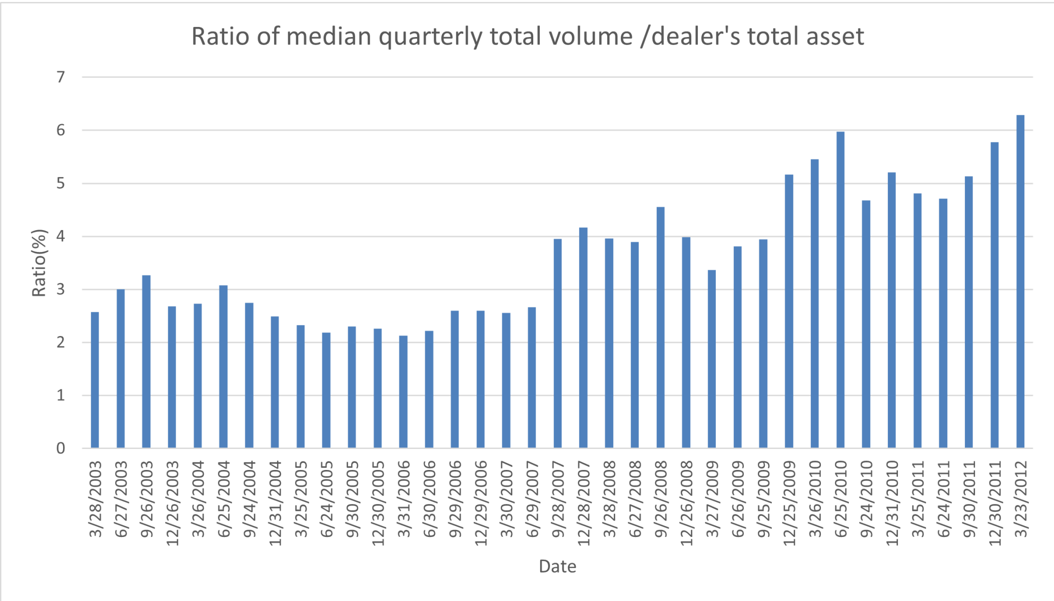


Figure 4.5 shows (the cross-sectional average) the bid-ask spread of our currencies (median quarterly). Bid-ask prices fell until the end of 2007 and then started to increase.

Figure 4.6: Ratio of Total Volume/ Dealer's Total Asset



In Figure 4.6, we computed the median, within each quarter, of the aggregate US$ FX volume relative to the dealers' total assets in that quarter.

Table 4.1: Summary of Volume

Panel A: First Dealer- Volume (billion$)					
Variables	N	Mean	S.D.	Min	Max
EUR	493	23.738	11.553	4.805	84.437
JPY	493	9.434	3.764	1.787	25.915
GBP	493	8.228	5.026	1.299	50.699
CHF	493	7.030	3.309	1.898	24.790
AUD	493	3.888	2.518	0.135	11.691
CAD	493	2.717	1.592	0.283	12.303
NZD	493	0.834	0.592	0.066	3.171
HKD	493	0.629	0.485	0.028	2.539
MXN	493	0.505	0.386	0.012	2.217
ZAR	493	0.491	0.424	0.010	2.395
SGD	493	0.455	0.333	0.015	1.790

Panel B: Second Dealer - Volume (billion$)					
Variables	N	Mean	S.D.	Min	Max
Leverage Volume	1,044	1.045	0.167	0.631	1.703
Real Money	1,044	1.112	0.137	0.650	1.626

Table 5.1 shows the summary of currencies. This table shows the number of observations, mean, standard deviation, minimum value and maximum value of the volume. All the currencies in Table 5.1 use USD as the base currency. Panel A shows our first dealer and Panel B shows our second dealer.

Table 4.2: Summary of Order Flow

Panel A: Aggregrated Order Flow -Second Dealer (billion$)							
Variables	N	Mean	S.D.	Min	Max	Skew	Kurt
EUR	1,044	-0.245	3.262	-12.331	8.125	-0.151	3.174
AUD	1,044	-0.483	4.948	-15.022	17.557	0.063	3.085
CAD	1,044	-0.009	5.729	-17.325	20.187	0.019	3.183
CHF	1,044	0.917	6.644	-22.856	21.291	-0.045	3.153
GBP	1,044	0.168	3.788	-14.742	11.637	-0.200	3.312
JPY	1,044	0.098	3.616	-10.790	12.785	0.181	3.264
NOK	1,044	-0.138	9.243	-29.638	33.424	-0.016	3.660
NZD	1,044	-0.201	6.140	-19.212	21.100	0.003	3.491
SEK	1,044	-0.171	7.864	-29.571	28.748	0.001	3.622
Panel B: Financial Order Flow -Second Dealer (billion$)							
Variables	N	Mean	S.D.	Min	Max	Skew	Kurt
EUR	1,044	0.065	3.193	-11.431	10.208	0.208	0.159
AUD	1,044	0.019	5.049	-13.350	17.732	0.818	0.377
CAD	1,044	0.645	5.623	-16.796	18.252	0.781	0.210
CHF	1,044	0.046	6.713	-27.823	20.831	0.023	0.058
GBP	1,044	0.343	3.726	-11.787	10.366	0.031	0.202
JPY	1,044	0.100	3.710	-11.729	12.649	0.246	0.586
NOK	1,044	1.004	9.223	-28.632	35.297	0.915	0.014
NZD	1,044	0.144	6.505	-22.191	22.270	0.520	0.007
SEK	1,044	0.270	7.832	-27.880	26.939	0.675	0.003
Panel C: Non-Financial Order Flow -Second Dealer (billion$)							
Variables	N	Mean	S.D.	Min	Max	Skew	Kurt
EUR	1,044	-0.309	1.371	-4.322	3.647	0.787	0.031
AUD	1,044	-0.502	1.665	-5.856	4.909	0.090	0.150
CAD	1,044	-0.654	1.639	-6.388	5.943	0.596	0.004
CHF	1,044	0.871	1.938	-6.572	6.855	0.746	0.179
GBP	1,044	-0.174	1.598	-5.889	4.614	0.827	0.747
JPY	1,044	-0.003	1.772	-5.367	5.463	0.059	0.586
NOK	1,044	-1.143	2.474	-9.009	9.156	0.000	0.000
NZD	1,044	-0.344	1.866	-6.473	6.609	0.677	0.914
SEK	1,044	-0.441	2.215	-6.768	6.330	0.243	0.018

Table 4.2 shows the summary of the order flow. This table shows the number of observations, mean, standard deviation, minimum value to maximum value, skew, and kurtosis. All the currencies in Table 4.2 use USD as the base currency.

Table 4.3: Excess Return and Normalized Volume - during and after financial crisis

start from Dec 2007 $ExcessReturn_t$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Volume		Bid-Ask Spread		Volatility	
		All Currencies		High	Low	High	Low	High	Low
$Return_{t-1}$	-0.1119**	-0.1028**	-0.1025**	-0.0411	-0.1310*	-0.1071*	-0.1017**	-0.1580***	0.0309
	0.0361	*0.0332*	*0.0340*	*0.0511*	*0.0630*	*0.0554*	*0.0298*	*0.0407*	*0.0474*
$Volume_{t-1}$	0.0018*	0.0027**	0.0027***	0.0018	0.0021	0.0030*	0.0011	0.0046***	-0.0004
	0.0009	*0.0009*	*0.0008*	*0.0015*	*0.0012*	*0.0015*	*0.0015*	*0.0012*	*0.0014*
$Return_{t-1} * Volume_{t-1}$		0.3738**	0.3694**	0.0944	0.4926**	0.3805*	0.5260	0.2566**	0.0564
		0.1411	*0.1465*	*0.2478*	*0.2131*	*0.1686*	*0.4110*	*0.1055*	*0.2339*
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj - R^2$	0.4337	0.4365	0.4361	0.4400	0.4563	0.3439	0.5544	0.4808	0.4141
Nobs	2,464	2,464	2,464	1,214	1,223	1,226	1,238	1,230	1,232

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 4.3 shows the coefficient results of the equation below:

$$r_t = A + Br_{t-1} + C(r_{t-1} \times nv_{t-1}) + Dnv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.6}$$

where $x_{i,t-1}$ controls for currency-pair-specific measures of liquidity and volatility. The coefficients A and ϕ denote currency pair and time fixed effects. In this model, we add the $(r_{i,t-1} \times nv_{i,t-1})$ interaction term. This table uses double-clustered standard errors and double fixed effects. We use the sample from December 2007 to March 2012. Columns (1) to (3) show the results when using all 11 currencies. Columns (4) - (9) split currencies according to median volume (4 and 5), median liquidity (6 and 7), and median volatility (8 and 9).

Table 4.4: Excess Return and Normalized Volume - before financial crisis

before financial crisis	$ExcessReturn_t$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Volume		Bid-Ask Spread		Volatility	
		All Currencies		High	Low	High	Low	High	Low
$Return_{t-1}$	0.0259	0.0229	0.0187	0.0101	0.0198	0.0259	0.0027	0.0003	0.1405
	0.0299	*0.0312*	*0.0322*	*0.0486*	*0.0372*	*0.0447*	*0.0391*	*0.0409*	*0.0448*
$Volume_{t-1}$	-0.0008	-0.0007	-0.0007	-0.0015	0.0000	-0.0009	-0.0003	-0.0011	-0.0005
	0.0007	*0.0008*	*0.0008*	*0.0014*	*0.0010*	*0.0009*	*0.0011*	*0.0016*	*0.0010*
$Return_{t-1} * Volume_{t-1}$		0.0869	0.0734	0.2243	-0.1710	0.1589	-0.4422	0.1211	-0.0182
		0.2659	*0.2569*	*0.3037*	*0.2417*	*0.2665*	*0.2751*	*0.3102*	*0.2007*
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.4531	0.453	0.4545	0.4133	0.5372	0.3593	0.5776	0.5016	0.4523
Nobs	2,904	2,904	2,904	1,438	1,442	1,444	1,460	1,451	1,453

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 4.4 shows the coefficient results of equation below:

$$r_t = A + Br_{t-1} + C(r_{t-1} \times nv_{t-1}) + Dnv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.7}$$

where $x_{i,t-1}$ controls for currency-pair-specific measures of liquidity and volatility. This table uses the sample from November 2002 to November 2007. Columns (1) to (3) show the results when using all 11 currencies. Columns (4) - (9) split currencies according to median volume (4 and 5), median liquidity (6 and 7), and median volatility (8 and 9).

Table 4.5: Change of Volume and Change of CDS - Financial Crisis

2008-2012	$\Delta Volume_t$
	(1)
$\Delta Volume_{t-1}$	-0.3735*** *0.0181*
ΔCDS_{t-1}	0.0315*** *0.0071*
ΔCDS_{t-2}	-0.0525*** *0.0129*
$adj-R^2$	0.1429
Nobs	2,442

Table 4.5 shows the weekly results when Y is the change of Volume and X is the lag change of volume and some lags of Δ CDS. This table uses currency fixed effects and currency standard error to do the panel regression.

Table 4.6: Change of Volume and Change of CDS - COVID-19

2018-2021	$\Delta Volume_t$		
	leverage volume (1)	real money (2)	sumvolume
ΔCDS_{t-1}	0.3152***	-0.0772	0.1296*
	0.0718	*0.0735*	*0.0695*
ΔCDS_{t-1}	-0.1928*	-0.0656	-0.2545
	0.1075	*0.1127*	*0.2074*
ΔCDS_{t-2}	-0.0730	0.1481	0.0789
	0.1317	*0.1462*	*0.2793*
ΔCDS_{t-3}	-0.2756**	-0.0680	-0.3894
	0.1173	*0.1290*	*0.2419*
ΔCDS_{t-4}	-0.2178*	-0.3077**	-0.5730**
	0.1219	*0.1368*	*0.2553*
$adj - R^2$	0.2106	0.0588	0.1026
Nobs	199	199	199

Table 4.6 shows the weekly results when Y is the change of Volume and X are the lag changes of volume and some lags of Δ CDS. This table uses robust standard errors to do the time series regression.

Table 4.7: Return and Normalized Volume - high and low groups

2007-2012

	(1) CDS High	(2) CDS Low	(3) LIBOR-OIS High	(4) LIBOR-OIS Low	(5) Leverage High	(6) Leverage Low	(7) Full Period
$Return_{t-1}$	-15.9905**	-7.3658**	-14.2596**	-9.5726**	-12.9708**	-12.5521**	-12.8688***
	5.4126	*2.6876*	*4.9351*	*3.4235*	*4.7985*	*3.9437*	*3.6044*
$Volume_{t-1}$	0.3420**	0.0042	0.3828**	-0.0763	0.2814	0.0507	0.1624
	0.1315	*0.1327*	*0.1356*	*0.1220*	*0.1637*	*0.1178*	*0.1082*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.414	0.329	0.3948	0.3704	0.4014	0.3369	0.3879
Nobs	1,232	1,232	1,221	1,243	1,232	1,232	2,464

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 4.7 shows results when logarithmic return is the dependent variable and normalised volume is the independent variable.

$$r_{i,t} = \alpha_0 + \beta_0 r_{t-1} + \beta_1 nv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.8}$$

We control for GARCH volatility and bid-ask spread. This table uses the sample from December 2007 to March 2012 using double fixed effects and double cluster standard errors. We split the sample into two parts according to the median of CDS Spread/ LIBOR-OIS Spread/ Leverage. The coefficient and standard error in this table are all multiplied by 100.

Table 4.8: Return and Normalized Volume - before financial crisis

2002-2007

	(1) CDS High	(2) CDS Low	(3) LIBOR-OIS High	(4) LIBOR-OIS Low	(5) Leverage High	(6) Leverage Low	(7) Full Period
$Return_{t-1}$	0.9810	-8.5468**	-1.7251	-5.5484*	-8.7362	1.7896	-2.7975
	4.4919	3.3376	4.5911	2.8992	5.5450	3.2769	*2.7864*
$Volume_{t-1}$	-0.1258	0.0578	-0.1061	0.0502	0.0497	-0.1135	-0.0495
	0.0857	0.0607	0.0931	0.0708	0.0831	0.0874	*0.0610*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.323	0.3802	0.3244	0.3719	0.296	0.3886	0.347
Nobs	1,441	1,463	1,430	1,474	1,452	1,452	2,904

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

In Table 4.8, we redo Table 4.7 by using the sample from November 2002 to November 2007, which is before the financial crisis. The coefficient and standard error in this table are all multiplied by 100.

Table 4.9: Return and Normalized Volume - high and low groups - Covid 19

2018-2021

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A : Leverage Volme							
	CDS		LIBOR-OIS		Leverage		Full
	High	Low	High	Low	High	Low	Period
$Return_{t-1}$	8.6534**	1.24531	9.8800**	0.26106	7.4340**	2.32	6.0901***
	2.8939	*0.9082*	*2.9979*	*0.8195*	*2.8174*	*1.3138*	*1.7436*
$Volume_{t-1}$	0.1377***	0.0373***	0.1250***	0.0266**	0.1532***	0.0413**	0.0897***
	0.0243	*0.0089*	*0.0302*	*0.0096*	*0.0229*	*0.0160*	*0.0185*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.0144	-0.0005	0.0166	-0.0014	0.0149	-0.0002	0.007
Nobs	3,771	3,744	3,744	3,771	3,753	3,762	7,515
Panel B : Real Money							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CDS		LIBOR-OIS		Leverage		Full
	High	Low	High	Low	High	Low	Period
$Return_{t-1}$	8.9229**	1.27788	10.2742**	0.25809	7.9755**	2.33847	6.2557***
	2.9888	*0.8752*	*3.0955*	*0.8178*	*2.9222*	*1.3114*	*1.8222*
$Volume_{t-1}$	0.1294***	0.0293**	0.1104**	0.02368	0.1111***	0.0437**	0.0738***
	0.0307	*0.0126*	*0.0356*	*0.0265*	*0.0195*	*0.0149*	*0.0115*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.0104	-0.0009	0.0121	-0.0015	0.0078	-0.0002	0.0048
Nobs	3,771	3,744	3,744	3,771	3,753	3,762	7,515
Panel C : Total Volume							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CDS		LIBOR-OIS		Leverage		Full
	High	Low	High	Low	High	Low	Period
$Return_{t-1}$	8.6722**	1.24755	9.9310**	0.25976	7.5523**	2.31891	6.1145***
	2.9268	*0.8902*	*3.0243*	*0.8186*	*2.8701*	*1.3143*	*1.7762*
$Volume_{t-1}$	0.0850***	0.0195***	0.0743***	0.01547	0.0855***	0.0257***	0.0515***
	0.0161	*0.0035*	*0.0193*	*0.0093*	*0.0130*	*0.0065*	*0.0090*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.0139	-0.0006	0.0157	-0.0014	0.0129	-0.0001	0.0065
Nobs	3,771	3,744	3,744	3,771	3,753	3,762	7,515

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 4.9 uses a panel regression with currency fixed effects and currency cluster standard errors.

$$r_{i,t} = \alpha_0 + \beta_0 r_{t-1} + \beta_1 nv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.9}$$

We split the sample into two parts according to the median of CDS Spread/ LIBOR-OIS Spread/ Leverage. This regression is similar to the one in Table 5; We use daily frequency during the COVID-19 period, which is from January 2018 to the end of 2021. The coefficient and standard error in this table are all multiplied by 100.

Table 4.10: Sub-sample results according to the CDS

	CDS percentile	beta
full sample	0	0.3738**
least constrained	0.2	0.0270
	0.4	0.1589
	0.6	0.4236**
most constrained	0.8	0.4506***

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 4.10 shows the coefficient (C) of $Return_{t-1} * Volume_{t-1}$ when we use the CDS as the constraint. We use the equation below without controls to run the double fixed regression with double cluster standard error.

$$r_t = A + Br_{t-1} + C(r_{t-1} \times nv_{t-1}) + Dnv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.10}$$

We sort the sample by decile according to the CDS value from smallest to largest. When the CDS percentile equals 0.0, this means we use the full sample. And when CDS percentile equals to 0.2 it means we use the first 20 % sub-sample and other percentiles are the same.

Appendices for Chapter 4

4A Different Volume Windows

The coefficient and standard error in this part are all multiplied by 100.

4A.1 window equals 8

Table 4.11: Return and Normalized Volume - during and after financial crisis

2007-2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CDS		LIBOR-OIS		Leverage		Full
	High	Low	High	Low	High	Low	Period
$Return_{t-1}$	-16.0239**	-7.3718**	-14.2294**	-9.5778**	-12.9678**	-12.5239**	-12.8698***
	5.4228	*2.6946*	*4.9530*	*3.4252*	*4.8063*	*3.9735*	*3.6132*
$Volume_{t-1}$	0.4264**	-0.0031	0.4392**	-0.0687	0.3748*	0.0339	0.1982*
	0.1499	*0.1261*	*0.1511*	*0.1110*	*0.1705*	*0.1081*	*0.1091*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj - R^2$	0.4147	0.329	0.3953	0.3704	0.4022	0.3368	0.3881
Nobs	1,232	1,232	1221	1,243	1,232	1,232	2,464

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

In Table 4.11, We show the results when we redo Table 4.7.

$$r_{i,t} = \alpha_0 + \beta_0 r_{t-1} + \beta_1 nv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.11}$$

We control for GARCH volatility and bid-ask spread. This table uses the sample from December 2007 to March 2012 using double fixed effects and double cluster standard errors. We split the sample into two parts according to the median of CDS Spread/ LIBOR-OIS Spread/ Leverage. The coefficient and standard error in this table are all multiplied by 100. In Table 4.11, we use the normalized volume, which was calculated by windows equal to 8.

Table 4.12: Return and Normalized Volume - before financial crisis

2002-2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CDS		LIBOR-OIS		Leverage		Full
	High	Low	High	Low	High	Low	Period
$Return_{t-1}$	0.9817	-8.5620**	-1.7369	-5.5657*	-8.7374	1.7844	-2.7921
	4.49287	3.34669	4.5907	2.90414	5.55344	3.28404	*2.7860*
$Volume_{t-1}$	-0.1534*	0.0720	-0.1290	0.0571	0.0393	-0.1224	-0.0625
	0.0834	0.0494	0.0885	0.0558	0.0894	0.0776	*0.0567*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj - R^2$	0.3233	0.3803	0.3246	0.3719	0.2959	0.3886	0.3471
Nobs	1,441	1,463	1,430	1,474	1,452	1,452	2,904

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

In Table 4.12, We show the results when we redo Table 4.8.

$$r_{i,t} = \alpha_0 + \beta_0 r_{t-1} + \beta_1 nv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.12}$$

We control for GARCH volatility and bid-ask spread. This table uses the sample from November 2002 to November 2007 using double fixed effects and double cluster standard errors. We split the sample into two parts according to the median of CDS Spread/ LIBOR-OIS Spread/ Leverage. The coefficient and standard error in this table are all multiplied by 100. In Table 4.12, we use the normalized volume, which was calculated by windows equals to 8.

4A.2 window equals 16

Table 4.13: Return and Normalized Volume - during and after financial crisis

2007-2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CDS		LIBOR-OIS		Leverage		Full
	High	Low	High	Low	High	Low	Period
$Return_{t-1}$	-15.9450**	-7.4169**	-14.2227**	-9.5607**	-12.9704**	-12.4750**	-12.8357***
	5.4150	*2.7032*	*4.9467*	*3.4253*	*4.7983*	*3.9815*	*3.6104*
$Volume_{t-1}$	0.3010**	-0.0458	0.3203**	-0.1180	0.25051	-0.0086	0.1157
	0.1304	*0.1198*	*0.1318*	*0.1061*	*0.1591*	*0.1097*	*0.1001*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj - R^2$	0.4137	0.3291	0.3942	0.3707	0.4013	0.3368	0.3877
Nobs	1,232	1,232	1221	1,243	1,232	1,232	2,464

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

In Table 4.13, We show the results when we redo Table 4.7.

$$r_{i,t} = \alpha_0 + \beta_0 r_{t-1} + \beta_1 nv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.13}$$

We control for GARCH volatility and bid-ask spread. This table uses the sample from December 2007 to March 2012 using double fixed effects and double cluster standard errors. We split the sample into two parts according to the median of CDS Spread/ LIBOR-OIS Spread/ Leverage. The coefficient and standard error in this table are all multiplied by 100. In Table 4.13, we use the normalized volume, which was calculated by windows equals to 16.

Table 4.14: Return and Normalized Volume - before financial crisis

2002-2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CDS		LIBOR-OIS		Leverage		Full
	High	Low	High	Low	High	Low	Period
$Return_{t-1}$	0.9561	-8.5538**	-1.7442	-5.5513*	-8.7533	1.7585	-2.8042
	4.4884	3.3379	4.5886	2.8959	5.5451	3.2629	*2.7875*
$Volume_{t-1}$	-0.1158	0.0677	-0.1007	0.0619	0.0739	-0.1123	-0.0389
	0.0883	0.0674	0.0953	0.0723	0.0845	0.0828	*0.0653*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.3229	0.3803	0.3244	0.372	0.2962	0.3886	0.347
Nobs	1,441	1,463	1,430	1,474	1,452	1,452	2,904

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

In Table 4.14, We show the results when we redo Table 4.8.

$$r_{i,t} = \alpha_0 + \beta_0 r_{t-1} + \beta_1 nv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.14}$$

We control for GARCH volatility and bid-ask spread. This table uses the sample from November 2002 to November 2007 using double fixed effects and double cluster standard errors. We split the sample into two parts according to the median of CDS Spread/ LIBOR-OIS Spread/ Leverage. The coefficient and standard error in this table are all multiplied by 100. In Table 4.14, we use the normalized volume, which was calculated by windows equals to 16.

4B Results without Quantitative Easing Period

The coefficient and standard error in this part are all multiplied by 100.

Table 4.15: Return and Normalized Volume - high and low groups - Before QE

2018-2021

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A : Leverage Volme							
	CDS		LIBOR-OIS		Leverage		Full
	High	Low	High	Low	High	Low	Period
$Return_{t-1}$	8.0431*	12.0863***	11.2651**	4.8474**	13.0271**	4.5550**	10.1916***
	4.2579	*1.5952*	*4.0371*	*1.6833*	*4.7911*	*1.8710*	*2.7657*
$Volume_{t-1}$	0.2473***	-0.0125	0.2072***	-0.0136	0.1343**	0.0224	0.0853**
	0.0582	0.0190	*0.0566*	*0.0147*	*0.0427*	*0.0293*	*0.0314*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.0226	0.0111	0.0266	0.0042	0.0254	-0.0007	0.0138
Nobs	2,070	2,142	2,106	2,106	2,106	2,106	4,212
Panel B : Real Money							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CDS		LIBOR-OIS		Leverage		Full
	High	Low	High	Low	High	Low	Period
$Return_{t-1}$	8.8372*	12.1055***	12.3544**	4.9864**	13.5772**	4.4447**	10.3284***
	4.4819	*1.5921*	*4.3590*	*1.6835*	*4.9902*	*1.8379*	*2.8619*
$Volume_{t-1}$	0.1347**	-0.0079	0.0938**	0.0257	0.0549	0.0729***	0.0612**
	0.0493	*0.0208*	*0.0403*	*0.0168*	*0.0408*	*0.0209*	*0.0264*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.0115	0.011	0.0159	0.0043	0.0187	0.0009	0.0117
Nobs	2,070	2,142	2,106	2,106	2,106	2,106	4,212
Panel C : Total Volume							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CDS		LIBOR-OIS		Leverage		Full
	High	Low	High	Low	High	Low	Period
$Return_{t-1}$	8.3941*	12.0959***	11.6676**	4.9232**	13.2899**	4.5253**	10.2344***
	4.3564	*1.5939*	*4.1718*	*1.6922*	*4.8836*	*1.8533*	*2.8041*
$Volume_{t-1}$	0.1112***	-0.0065	0.0990**	0.0007	0.0605**	0.0280*	0.0455**
	0.0307	*0.0105*	*0.0309*	*0.0086*	*0.0240*	*0.0145*	*0.0173*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.0176	0.011	0.0221	0.004	0.0221	0.0001	0.0131
Nobs	2,070	2,142	2,106	2,106	2,106	2,106	4,212

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 4.15 redo the table 4.9 by using the sample period before quantitative easing.

$$r_{i,t} = \alpha_0 + \beta_0 r_{t-1} + \beta_1 nv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.15}$$

We control for GARCH volatility and bid-ask spread. In this table, we use a daily sample from January 2018 to March 2020 and still use the currency fixed effect and currency cluster standard error to do the panel regression.

4C Different Maturity for Forward Rates

Table 4.16: Excess Return and Normalized Volume - using 1-month forward rate

start from Dec 2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Volume		Bid-Ask Spread		Volatility	
	All Currencies			High	Low	High	Low	High	Low
$Return_{t-1}$	-0.1086**	-0.0971**	-0.1005**	-0.0169	-0.1312*	-0.0947	-0.1123**	-0.1661***	0.0019
	0.0415	*0.0373*	*0.0381*	*0.0772*	*0.0657*	*0.0539*	*0.0360*	*0.0400*	*0.0513*
$Volume_{t-1}$	0.0013	0.0018	0.0019	-0.0004	0.0020	0.0022	0.0003	0.0050**	-0.0010
	0.0014	*0.0013*	*0.0012*	*0.0019*	*0.0021*	*0.0021*	*0.0016*	*0.0018*	*0.0014*
$Return_{t-1} * Volume_{t-1}$		0.5376***	0.5448***	-0.0242	0.6465***	0.5945**	0.6944	0.4102**	0.0997
		0.1456	*0.1497*	*0.3830*	*0.1720*	*0.1710*	*0.4876*	*0.1245*	*0.2988*
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj - R^2$	0.3753	0.3809	0.3807	0.3873	0.4027	0.2225	0.5472	0.4493	0.3521
Nobs	2,016	2,016	2,016	984	995	1,002	1,014	1,002	1,008

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 4.16 uses the 1-month forward rate to calculate excess return. In this table, we use Euro(EUR), Japanese yen (JPY), Swiss franc (CHF), Australian dollar (AUD), New Zealand dollar (NZD), Canadian dollar (CAD), South African rand (ZAR), Singapore dollar (SGD), Hong Kong dollar (HKD) as our sample.

$$r_t = A + Br_{t-1} + C(r_{t-1} \times nv_{t-1}) + Dnv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.16}$$

where $x_{i,t-1}$ controls for currency-pair-specific measures of liquidity and volatility. The coefficients A and ϕ denote currency pair and time fixed-effects. In this model, we add the $(r_{i,t-1} \times nv_{i,t-1})$ interaction term. This table uses double-clustered standard error and double fixed effect. We use the sample from December 2007 to March 2012. Columns (1) to (3) show the results when using all 11 currencies. Columns (4) - (9) split currencies according to median volume (4 and 5), median liquidity (6 and 7), and median volatility (8 and 9).

Table 4.17: Excess Return and Normalized Volume - using 1-week forward rate

start from Dec 2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Volume		Bid-Ask Spread		Volatility	
		All Currencies		High	Low	High	Low	High	Low
$Return_{t-1}$	-0.0948*	-0.0841	-0.0861*	0.0280	-0.1565*	-0.0847	-0.0834	-0.1193*	-0.0275
	0.0473	*0.0443*	*0.0433*	*0.0810*	*0.0788*	*0.0757*	*0.0510*	*0.0504*	*0.0622*
$Volume_{t-1}$	-0.0008	-0.0010	-0.0011	-0.0014	0.0003	0.0006	-0.0005	-0.0015	0.0009
	0.0012	*0.0011*	*0.0011*	*0.0024*	*0.0016*	*0.0018*	*0.0018*	*0.0019*	*0.0018*
$Return_{t-1} * Volume_{t-1}$		0.5054**	0.5056**	0.0024	0.6445**	0.3447	0.7892	0.4261**	0.2195
		0.1662	*0.1700*	*0.5412*	*0.1985*	*0.2689*	*0.3982*	*0.1582*	*0.2241*
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj - R^2$	0.2305	0.236	0.2357	0.2271	0.2057	0.0009	0.439	0.2204	0.2793
Nobs	1,568	1,568	1,568	755	765	764	804	783	784

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 4.17 uses the 1-week forward rate to calculate excess return. In this table, we use the Japanese yen (JPY), British pound (GBP), Swiss franc (CHF), Canadian dollar (CAD), South African rand (ZAR), Singapore dollar (SGD), Hong Kong dollar (HKD) as our sample.

$$r_t = A + Br_{t-1} + C(r_{t-1} \times nv_{t-1}) + Dnv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.17}$$

where $x_{i,t-1}$ controls for currency-pair-specific measures of liquidity and volatility. The coefficients A and ϕ denote currency pair and time fixed effects. In this model, we add the $(r_{i,t-1} \times nv_{i,t-1})$ interaction term. This table uses double-clustered standard errors and double fixed effects. We use the sample from December 2007 to March 2012. Columns (1) to (3) show the results when using all 11 currencies. Columns (4) - (9) split currencies according to median volume (4 and 5), median liquidity (6 and 7), and median volatility (8 and 9).

4D Realized Volatility

This section uses the realized volatility instead of the GARCH volatility.

Table 4.18: Excess Return and Normalized Volume - during and after financial crisis

start from Dec 2007	$ExcessReturn_t$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Volume		Bid-Ask Spread		Volatility	
		All Currencies		High	Low	High	Low	High	Low
$Return_{t-1}$	-0.1119**	-0.1028**	-0.1186***	-0.0610	-0.1442**	-0.1394**	-0.097**	-0.1770***	-0.0291
	0.0361	*0.0332*	*0.0323*	*0.0436*	*0.0603*	*0.0503*	*0.0329*	*0.0390*	*0.0192*
$Volume_{t-1}$	-0.0018*	-0.0027**	-0.0029**	-0.0019	-0.0019	-0.0028*	-0.0009	-0.0039**	-0.0005
	0.0009	*0.0009*	*0.0010*	*0.0015*	*0.0012*	*0.0013*	*0.0014*	*0.0014*	*0.0007*
$Return_{t-1} * Volume_{t-1}$		0.3738**	0.3865**	0.1188	0.4622*	0.3604*	0.4737	0.3199	-0.0196
		0.1411	*0.1606*	*0.2397*	*0.2385*	*0.1674*	*0.3762*	*0.1940*	*0.1098*
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.4337	0.4365	0.4579	0.4494	0.4767	0.3754	0.5634	0.5478	0.572
Nobs	2,464	2,464	2,464	1,214	1,223	1,226	1,238	1,227	1,221

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 4.18 uses the realized volatility to redo Table 4.3.

$$r_t = A + Br_{t-1} + C(r_{t-1} \times nv_{t-1}) + Dnv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.18}$$

where $x_{i,t-1}$ controls for currency-pair-specific measures of liquidity and volatility. The coefficients A and ϕ denote currency pair and time fixed-effects. In this model, we add the $(r_{i,t-1} \times nv_{i,t-1})$ interaction term. This table uses double-clustered standard error and double fixed effect. We use the sample from December 2007 to March 2012. Columns (1) to (3) show the results when using all 11 currencies. Columns (4) - (9) split currencies according to median volume (4 and 5), median liquidity (6 and 7), and median volatility (8 and 9).

Table 4.19: Excess Return and Normalized Volume - before financial crisis

before financial crisis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Volume		Bid-Ask Spread		Volatility	
	All Currencies			High	Low	High	Low	High	Low
$Return_{t-1}$	0.0259	0.0229	0.0120	0.0004	0.0275	0.0128	0.0038	-0.0111	0.0264
	0.0299	*0.0312*	*0.0326*	*0.0456*	*0.0338*	*0.0434*	*0.0402*	*0.0439*	*0.0277*
$Volume_{t-1}$	0.0008	0.0007	0.0007	0.0014	0.0000	0.0009	0.0003	0.0034	0.0001
	0.0007	*0.0008*	*0.0008*	*0.0013*	*0.0010*	*0.0011*	*0.0011*	*0.0016*	*0.0009*
$Return_{t-1} * Volume_{t-1}$		0.0869	0.0510	0.1600	-0.1672	0.1201	-0.4336	0.1731	-0.1006
		0.2659	*0.2498*	*0.2806*	*0.2539*	*0.2506*	*0.2724*	*0.3238*	*0.0944*
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj - R^2$	0.4531	0.453	0.4600	0.4365	0.5412	0.3743	0.5777	0.5539	0.6662
Nobs	2,904	2,904	2,904	1,438	1,442	1,444	1,460	1,442	1,449

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 4.19 uses the realized volatility to redo Table 4.4.

$$r_t = A + Br_{t-1} + C(r_{t-1} \times nv_{t-1}) + Dnv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.19}$$

where $x_{i,t-1}$ controls for currency-pair-specific measures of liquidity and volatility. The coefficients A and ϕ denote currency pair and time fixed effects. In this model, we add the $(r_{i,t-1} \times nv_{i,t-1})$ interaction term. We use the sample from November 2002 to November 2007. Columns (1) to (3) show the results when using all 11 currencies. Columns (4) - (9) split currencies according to median volume (4 and 5), median liquidity (6 and 7), and median volatility (8 and 9).

4E Second Dealer Results

Table 4.20: Excess Return and Normalized Volume - Covid

2018-2021

Panel A : Leverage Volume									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Volume		Bid-Ask Spread		Volatility	
		All Currencies		High	Low	High	Low	High	Low
$Return_{t-1}$	0.5092	1.4592***	1.3561***	1.3720***	1.1483***	1.4788***	0.4089*	1.5268***	0.0048
	0.2953	*0.1108*	*0.1062*	*0.2954*	*0.0929*	*0.1480*	*0.1730*	*0.0653*	*0.4184*
$Volume_{t-1}$	0.0020***	0.0046***	0.0047***	0.0100***	-0.0011	0.0052**	0.0041***	0.0057**	0.0029**
	0.0006	*0.0012*	*0.0012*	*0.0029*	*0.0014*	*0.0019*	*0.0007*	*0.0021*	*0.0010*
$Return_{t-1} * Volume_{t-1}$		-0.8509***	-0.7696***	-0.8045***	-0.5344**	-0.7775*	-0.4377**	-0.8719**	-0.0200
		0.2350	*0.1766*	*0.1055*	*0.1881*	*0.3416*	*0.1410*	*0.2617*	*0.4049*
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj - R^2$	0.3132	0.3508	0.3612	0.2279	0.5218	0.4818	0.0548	0.4334	0.0348
Nobs	1,827	1,827	1,827	918	909	890	937	913	914

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

2018-2021

Panel B : Real Money									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Volume		Bid-Ask Spread		Volatility	
	All Currencies			High	Low	High	Low	High	Low
$Return_{t-1}$	0.5096	1.3303***	1.1635***	1.2313***	0.3144	1.3529***	0.6393**	1.4209***	-0.0065
	0.2949	*0.1752*	*0.1462*	*0.2739*	*0.2387*	*0.2010*	*0.2182*	*0.1118*	*0.4497*
$Volume_{t-1}$	0.0016**	0.0034*	0.0044**	0.0077**	0.0059***	0.0051*	0.0051***	0.0045	0.0034***
	0.0006	*0.0016*	*0.0016*	*0.0030*	*0.0012*	*0.0024*	*0.0007*	*0.0032*	*0.0007*
$Return_{t-1} * Volume_{t-1}$		-0.6796**	-0.5542**	-0.6172**	0.2765***	-0.6119	-0.6145**	-0.7171**	-0.0086
		0.2785	*0.2213*	*0.2253*	*0.0662*	*0.3492*	*0.1712*	*0.2685*	*0.4070*
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj - R^2$	0.3125	0.3295	0.3424	0.2628	0.4614	0.4648	0.0589	0.4116	0.0339
Nobs	1,827	1,827	1,827	918	909	890	937	913	914

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 4.20 shows the results of Table 4.3 when using the Covid period (2018-2021).

$$r_t = A + Br_{t-1} + C(r_{t-1} \times nv_{t-1}) + Dnv_{t-1} + \lambda x_{t-1} + \phi + E_{t-1} \tag{4.20}$$

where $x_{i,t-1}$ controls for currency-pair-specific measures of liquidity and volatility. The coefficients A and ϕ denote currency pair fixed-effects. In this model, we add the $(r_{i,t-1} \times nv_{i,t-1})$ interaction term. This table uses currency-clustered standard error. Columns (1) to (3) show the results when using all 11 currencies. Columns (4) - (9) split currencies according to median volume (4 and 5), median liquidity (6 and 7), and median volatility (8 and 9).

4F Order Flow as Control

The coefficient and standard error in this part are all multiplied by 100.

Table 4.20: Order Flow as Control - during and after financial crisis

2007-2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CDS		LIBOR-OIS		Leverage		Full
	High	Low	High	Low	High	Low	Period
$Return_{t-1}$	-15.9928**	-7.3278**	-14.2252**	-9.5856**	-12.9614**	-12.7063***	-12.8442***
	5.3878	*3.1307*	*4.9040*	*3.3965*	*4.7251*	*3.8601*	*3.5799*
$Volume_{t-1}$	0.3419**	-0.0053	0.3823**	-0.0788	0.2816	0.0413	0.1611
	0.1288	*0.1362*	*0.1375*	*0.1224*	*0.1595*	*0.1175*	*0.0011*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Order Flow Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.4135	0.3307	0.3944	0.3703	0.4009	0.3379	0.3879
Nobs	1,232	1,232	1,221	1,243	1,232	1,232	2,464

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 4.20 adds order flow as a control to redo Table 4.7, and the main results do not change.

$$r_{i,t} = \alpha_0 + \beta_0 r_{t-1} + \beta_1 nv_{t-1} + \lambda x_{t-1} + \theta OF_{t-1} + \phi + E_{t-1} \tag{4.21}$$

We control for GARCH volatility and bid-ask spread. This table uses the sample from 2007 to 2012, using double fixed effects and double cluster standard errors. We split the sample into two parts according to the median of CDS Spread/ LIBOR-OIS Spread/ Leverage. The coefficient and standard error in this table are all multiplied by 100.

Table 4.21: Order Flow as Control - Covid-19

2018-2021

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A : Leverage Volme							
	CDS		LIBOR-OIS		Leverage		Full
	High	Low	High	Low	High	Low	Period
$Return_{t-1}$	8.9029**	1.4604	10.2347***	0.3892	7.5747**	2.7209*	6.3365***
	2.8520	*0.9885*	*2.8947*	*0.8575*	*2.8508*	*1.4422*	*1.7435*
$Volume_{t-1}$	0.1375***	0.0372***	0.1256***	0.0258**	0.1527***	0.0414**	0.0895***
	0.0248	*0.0088*	*0.0303*	*0.0095*	*0.0230*	*0.0154*	*0.0185*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Order Flow Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.0179	0.0005	0.0203	-0.0004	0.0173	0.0018	0.0094
Nobs	3,771	3,744	3,744	3,771	3,753	3,762	7,515
Panel B : Real Money							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CDS		LIBOR-OIS		Leverage		Full
	High	Low	High	Low	High	Low	Period
$Return_{t-1}$	9.1725**	1.4932	10.6287***	0.3863	8.1119**	2.7426*	6.5023***
	2.9431	*0.9593*	*2.9938*	*0.8568*	*2.9566*	*1.4378*	*1.8215*
$Volume_{t-1}$	0.1288**	0.0289*	0.1110**	0.0225	0.1098***	0.0439**	0.0732***
	0.0318	*0.0132*	*0.0360*	*0.0273*	*0.0200*	*0.0150*	*0.0117*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Order Flow Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.0138	0.0002	0.0158	-0.0005	0.0103	0.0018	0.0087
Nobs	3,771	3,744	3,744	3,771	3,753	3,762	7,515
Panel C : Total Volume							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CDS		LIBOR-OIS		Leverage		Full
	High	Low	High	Low	High	Low	Period
$Return_{t-1}$	8.9217**	1.4627	10.2855***	0.3877	7.6884**	2.7230*	6.3610***
	2.8833	*0.9725*	*2.9216*	*0.8570*	*2.9031*	*1.4417*	*1.7757*
$Volume_{t-1}$	0.0848***	0.0194***	0.0747***	0.0149	0.0850***	0.0257***	0.0513***
	0.0166	*0.0036*	*0.0194*	*0.0096*	*0.0131*	*0.0063*	*0.0090*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Order Flow Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$adj-R^2$	0.0174	0.0004	0.0194	-0.0004	0.0153	0.002	0.009
Nobs	3,771	3,744	3,744	3,771	3,753	3,762	7,515

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 4.21 adds order flow as a control to redo Table 4.9, and the main results do not change.

$$r_{i,t} = \alpha_0 + \beta_0 r_{t-1} + \beta_1 nv_{t-1} + \lambda x_{t-1} + \theta OF_{t-1} + \phi + E_{t-1} \tag{4.22}$$

We control for GARCH volatility and bid-ask spread. This table uses the sample from 2018 to 2021, using currency fixed effects and currency cluster standard errors. We split the sample into two parts according to the median of CDS Spread/ LIBOR-OIS Spread/ Leverage. The coefficient and standard error in this table are all multiplied by 100.

Chapter 5

Dealer Balance-Sheet Constraints and the Dollar Supply-Demand Curve

Abstract: We employ two unique FX volume and order flow datasets from two large dealer banks and study how dealer balance-sheet frictions affect price formation in the FX spot market. Our empirical evidence shows that volume has a substantially larger price impact when dealers' balance-sheet frictions are tighter. We focus on debt overhang costs (Myers (1977)) related to the equity holders of the bank when the dealer supplies FX dollar liquidity during shocks. We study the 2008 financial crisis and the 2020 COVID-19 shock. We directly estimate the slope of the dollar supply curve and show that it steepens with dealer balance-sheet stress. Event-time analysis around CDS shocks confirms that FX prices respond sharply to trading pressure only when balance-sheet constraints and volume are jointly high, with no pre-trends. On the demand side, we show that surges in dollar demand during crises come from leveraged financial clients whose trading is sensitive to dealer capital conditions. This capital-dependent demand interacts with the steepened supply curve to amplify price impact. We present a model explaining the mechanism.
Keywords: JEL Financial Crises(G01); Asset Pricing, Trading Volume, Bond Interest Rates(G12); International Financial Markets(G15); Foreign Exchange(F31)

5.1 Introduction

How do dealer balance-sheet frictions affect price formation in foreign exchange markets? A large and growing literature shows that financial intermediaries are central to asset pricing. When dealer capital is scarce, intermediation becomes more costly, and asset prices respond to changes in intermediaries' ability to absorb risk or expand their balance sheets (Adrian et al. (2015); He et al. (2017); Duffie (2010); Duffie et al. (2023); He et al. (2022)). This chapter explores whether these frictions will alter the supply and demand curves of foreign exchange prices and amplify the impact of trading pressures on prices. We examine this mechanism in the world's largest financial market: the foreign exchange spot market for U.S. dollars.

Our central result is that dealer balance-sheet constraints make the supply of dollar liquidity more inelastic. When dealer balance sheets are constrained, the same amount of FX spot dollar trading volume generates a substantially larger exchange-rate response. We show that this state-dependent price impact reflects a steepening of the dollar supply curve driven by debt overhang costs borne by bank equity holders. This mechanism differs from the standard view that balance-sheet constraints operate primarily through quantity rationing or market withdrawal. Instead, constrained dealers continue to intermediate client trades, but only at worse prices.

Our analysis is motivated by a broader empirical pattern documented in earlier work. FX spot trading volume becomes informative about exchange rate movements primarily during periods of financial stress in the post-2008 era. In this paper, we take this regime dependence as a starting point and focus on the mechanism behind it. We use two proprietary bilateral over-the-counter FX datasets from two of the largest global FX dealers. These data span periods both before and after the Global Financial Crisis (GFC). They allow us to observe dealer-level FX spot volumes and matched order flows disaggregated by client type over nearly two decades. We use these data to study how dealer balance-sheet constraints shape the price impact of trading volume and the elasticity of dollar supply.

Our core contribution is to identify and explain a supply-demand interaction mechanism through which dealer balance-sheet frictions affect exchange rates. We proxy dealer balance-sheet stress using dealer CDS spreads (Andersen et al. (2019); Cerrato and Mei (2025)), leverage measures from He et al. (2017), and market-wide funding stress such as the LIBOR-OIS spread. We show that, following 2008, these frictions raise the shadow cost of expanding balance sheets to intermediate FX spot transactions. As debt overhang costs rise, the supply curve for dollar liquidity becomes steeper. Given the same quantity pressure, prices move more. FX trading volume therefore matters not because it necessarily reveals private information, but because its price impact depends on the balance-sheet capacity of intermediaries.

We provide three pieces of direct empirical evidence for this supply-demand mechanism. First, we directly estimate the slope of the dollar supply curve by interacting the normalised volume with dealer CDS spreads. We show that the implied slope rises steeply after the financial crisis and the COVID-19 shock. During normal times, the slope was flat and insignificant. Rolling-window regressions confirm that the covariance between the interaction term and the estimated coefficient is positive during stress periods and insignificant otherwise.

Secondly, we use changes in CDS spreads to identify exogenous shocks to balance-sheet constraints. We construct a joint-state indicator that equals one when both balance-sheet constraints and trading volume are high. Event-time analyses reveal that FX prices respond sharply to trading pressure only in this joint state. There are no pre-trends, and there is no comparable response outside the joint state. This dynamic evidence directly identifies supply-curve steepening. Prices respond strongly to quantities only when the marginal cost of intermediation is high.

Third, we document a complementary demand-side channel. Using detailed order-flow data disaggregated by client type, we show that surges in dollar demand during crises originate primarily from leveraged financial clients. We further show that changes in dealer capital predict subsequent changes in client flows. Leveraged clients prefer trading with dealers whose capital is higher, consistent with intense competition among large FX dealers (Duffie (2010); Butz and Oomen (2019); Krohn and Sushko (2022)). Non-financial client flows are not related to the capital of the dealer. This capital-dependent demand, interacting with the steepened supply curve, amplifies the price impact of volume. Furthermore, it generates the observed positive correlation between FX volume and dollar appreciation during periods of stress.

These results collectively provide consistent evidence that the price impact of foreign exchange trading volume is influenced by both supply and demand. Excessive dealer debt drives a steepening of the supply curve. Increased demand for currency from leveraged financial clients also shifts the demand curve.

To rationalise our empirical findings, we develop a simple model of FX spot intermediation. In this model, a risk-neutral dealer faces leverage constraints and debt overhang costs. Following Myers (1977) and Andersen et al. (2019), debt overhang arises because expanding balance sheets transfers value from equity holders to creditors when funding costs are high. In the model, the debt overhang cost directly maps into the slope of the dollar supply curve. The model generates three testable predictions. The slope of the dollar supply curve increases with dealer balance-sheet stress. FX prices respond to trading pressure only in the joint state of high constraints and high volume. Dollar demand from leveraged clients is sensitive to dealer capital, while non-financial client flows are not.

It is important to distinguish the mechanism we study from the standard balance-sheet-constraint view of intermediation. The existing literature primarily treats intermediary capital scarcity as a state variable captured by leverage, net worth, or a shadow cost of capital (He et al. (2017); Adrian et al. (2015)). We focus on incentives and study how equity holders respond to capital scarcity when pricing intermediation. When equity is scarce, expanding the balance sheet transfers value to existing creditors, generating a debt-overhang incentive distortion that directly affects quotes (Andersen et al. (2019); Cerrato and Mei (2025)). In standard balance-sheet-constraint models, tighter constraints often lead to reduced intermediation or quantity rationing. In contrast, a debt-overhang mechanism operating through equity-holder incentives leads to continued intermediation but at higher prices: the supply curve steepens, price impact rises, but trading volume need not collapse. These predictions align closely with the empirical patterns we document in FX markets during periods of stress and are supported by our model.

Our interpretation departs from the dominant view in the FX-volume literature. That literature emphasises asymmetric information and demand-side learning as the source of volume predictability (Llorente et al. (2002); Cespa et al. (2022b)). While such mechanisms may be present, they cannot explain why the price impact of volume is negligible before 2008 or why it rises sharply only in periods of severe dealer balance-sheet stress. Our analysis is closely related to recent work on FX predictability and trading activity by Cespa et al. (2022b), Cenedese et al. (2021), and Ranaldo and Santucci de Magistris (2019). These papers document important links between FX returns, volume, and investor behaviour. Our contribution is complementary but distinct. We show that the price impact of FX volume increases with dealer balance-sheet stress and that this increase reflects a steepening of the dollar supply curve driven by debt overhang costs.

Our results connect several strands of the literature. First, they complement recent work documenting increased FX liquidity costs and steeper supply curves in the post-crisis era (Czech et al. (2021); Huang et al. (2025); Kloks et al. (2023)). We shift the focus from regulatory constraints to debt overhang costs borne by equity holders. Second, our results relate to studies of dollar funding shortages and financial channels of exchange rates (Bruno and Shin (2015); Du et al. (2018a); Jiang et al. (2021); Kekre and Lenel (2024)). We show that the price impact of spot FX volume reflects these frictions when intermediation capacity is constrained. Third, our results complement evidence on the failure of covered interest parity during crises (Du et al. (2018b); Burnside and Cerrato (2025b)) by documenting analogous mechanisms in the spot FX market.

More broadly, our findings have implications for financial stability and policy. They suggest that FX markets become more fragile when dealer balance sheets are impaired by debt overhang, as quantity shocks translate into disproportionately large price movements. This insight is crucial for understanding foreign exchange market stress and assessing the effectiveness of central bank intervention when dollar liquidity is scarce. (Ferreira et al. (2024)). Our model further implies that higher equity capital, while costly for shareholders in the short run, can enhance future profitability by easing intermediation constraints, echoing arguments in Admati et al. (2012).

Finally, this paper demonstrates that trader balance sheet frictions affect trading volume and price formation in the foreign exchange market. By combining proprietary dealer data, event-based identification, and a structural interpretation grounded in debt overhang, we provide new evidence on how post-crisis financial frictions alter price formation in the world's largest financial market.

5.2 Balance Sheet Frictions, Debt Overhang, and the Dollar Supply Curve

This section develops the institutional and economic framework that motivates our empirical identification strategy and theoretical model. We begin by describing how FX spot intermediation works in practice. We then explain how debt overhang costs arise in this context and why they steepen the dollar supply curve. We conclude by stating three testable predictions that we take to the data in subsequent sections.

5.2.1 *FX Spot Intermediation: Institutional Background*

The foreign exchange spot market is an over-the-counter (OTC) bilateral market. A small number of large dealer banks intermediate the vast majority of spot transactions (Krohn and Sushko (2022)). These dealers act as marginal price setters. They quote prices to clients, absorb order flow, and manage the resulting inventory on their balance sheets. Their balance sheets are the primary source of US dollar liquidity in the spot market. Any pressure on these balance sheets, therefore, has direct consequences for dollar intermediation. Duffie et al. (2023) make an analogous case for the US Treasury market.

From the dealer's perspective, the intermediation of spot OTC dollar transactions is similar to the intermediation of a dollar derivative position such as a swap. However, there are two important differences. First, balance-sheet imbalances from spot FX inventory are generally financed through the bank's treasury at the bank's own credit spread. Before 2008, dealers could fund these positions close to the risk-free rate. After 2008, this is no longer the case. Second, FX spot transactions involve very large notional amounts settled two business days after the trade (Chaboud et al. (2023)). Funding costs for FX spot can therefore be significantly higher than in the FX swap market. The dealer must deploy substantial capital to fund these positions unless she can offset them through a matching book or the interdealer market.

There is strong evidence that dealers' desks rely on internal capital markets to fund their intermediation activity (Lu et al. (2023)). This reliance increases during periods of market stress, when external funding becomes more expensive. However, internal capital is also scarce during turmoil. Banks allocate capital to trading desks on a daily basis. Borrowing additional capital from the treasury or externally is very expensive. As a result, dealers try to run matching books with clients as much as possible during stress periods. This reduces the consumption of capital but also limits their ability to supply dollar liquidity on demand.

The post-2008 era brought a structural increase in funding costs for large dealer banks. Regulatory changes such as the Dodd-Frank Act contributed to this increase (Berndt et al. (2024)). Credit spreads for major dealers rose and remained persistently higher than before 2008. These persistent cost increases have intensified capital structure frictions throughout the banking sector. They affect not only derivatives intermediation but also the provision of spot FX liquidity (Du et al. (2023); Andersen et al. (2019)).

5.2.2 *Debt Overhang in the FX Dollar Market*

We now explain how these institutional features give rise to debt overhang costs that affect FX intermediation. We use the term debt overhang in the Myers marginal-incentive sense (Myers (1977)). The core idea is straightforward. When a firm carries high leverage, any balance-sheet expansion generates a wealth transfer to existing creditors. Equity holders bear the cost of expansion but do not capture all the benefits. They therefore demand compensation, leading to underinvestment relative to the first-best outcome. Admati et al. (2018) show that this distortion is self-reinforcing. Once leverage is high, equity holders resist recapitalisation because the benefits accrue disproportionately to creditors.

Andersen et al. (2019) applies this framework directly to dealer intermediation in derivatives markets. They demonstrate that the funding value adjustment (FVA) charged by dealers to OTC clients represents a wealth transfer from equity to creditors. The magnitude of this transfer is captured by the dealer's CDS spread. A higher CDS spread implies a larger debt overhang wedge. In that situation, equity holders require greater compensation before agreeing to expand intermediation. Cerrato and Mei (2025) develops a balance-sheet model that formalises this mechanism. They show how it maps into observable pricing distortions. Burnside and Cerrato (2025b) use a CDS-based index of the 12 largest global dealer banks to proxy for debt overhang costs when studying covered interest rate parity violations.[1]

Consider how this applies to FX spot intermediation. Figure 5.8 shows a simplified balance sheet of an FX dealer. The dealer has US dollar lending on one side and US dollar borrowing on the other. Customers demand and offer US dollars. The liability side consists of liabilities financed externally (via the US dollar repo market or commercial paper) or internally (generally uncollateralised borrowing via the treasury).

Now suppose that an exogenous shock reduces the equity capital of the dealer. At the same time, demand for US dollars from clients surges. The balance sheet shows an imbalance between dollar demand from clients and available financing resources. To accommodate this demand, the dealer must commit her own capital. However, she is reluctant to do so when capital is already low. Committing additional capital transfers value to existing creditors. This is the debt overhang problem. Duffie et al. (2023) document this behaviour in the Treasury market. Dealers post large bid-ask spreads to recover these costs or to avoid being hit by customer flows. Adrian et al. (2017) makes a similar case. They relate it to higher regulatory capital requirements after 2008.

We use the term debt overhang broadly in this paper. We do not require that

[1] This index is constructed as an equal-weighted average of CDS spreads for the 12 largest US and European dealers. It is highly liquid and not subject to manipulation by any single institution. It captures the funding costs that dealers pass on to clients when providing OTC liquidity.

regulatory or leverage constraints mechanically bind. Our friction is a capital structure incentive distortion that affects pricing. Even when balance-sheet constraints are slack, equity holders may still face a private cost of expansion because part of the surplus accrues to creditors. This is a pricing distortion rather than a hard constraint on quantities. This distinction is important. Standard balance-sheet-constraint models predict that tight constraints lead to reduced intermediation or quantity rationing. Our mechanism predicts something different. Intermediation may continue during stress, but at higher prices. The supply curve steepens rather than shifting inward. Trading volume need not collapse.

5.2.3 *How Debt Overhang Steepens the Dollar Supply Curve*

We now connect debt overhang to the slope of the dollar supply curve. This is the central economic argument of the paper.

Consider Figure 5.9 (a,b). In normal times, the dealer can supply dollar liquidity at relatively stable prices. The supply curve is flat. Demand shocks move quantities but have limited price impact. After 2008, debt overhang costs rise. The supply curve becomes steeper. The same demand shock now generates a larger price impact. The exchange rate appreciates more for any given increase in dollar demand.

What steepens the supply curve? The debt overhang wedge. When equity is scarce, the dealer requires a larger price concession per unit of intermediation. Each additional unit of dollar supply imposes a private cost on equity holders because it expands the balance sheet and transfers value to creditors. This cost increases with the severity of debt overhang. It is proxied empirically by the dealer CDS spread, intermediary leverage, and the LIBOR-OIS spread.

This mechanism also explains why volume and constraints can both increase simultaneously during stress. A rise in FX volatility drives up the demand for US dollars for any given supply. This surge in demand can be related to increases in the convenience yield (Du et al. (2018a)), macroeconomic factors, or a dash for cash during crises. The inelastic supply of dollars is related to dollar funding costs (Du et al. (2018b)). When volatility increases, higher demand for dollars, combined with reduced willingness to intermediate, drives up both FX volumes and price impact. Debt overhang does not imply a monotonic decline in aggregate volume. Instead, it alters how quantity pressure is accommodated. It affects the price impact of trades rather than mechanically reducing trading activity.

On the demand side, there is an important asymmetry across client types. Leveraged financial clients are price-sensitive and prefer to trade with dealers whose capital is higher (Duffie (2010); Butz and Oomen (2019); Krohn and Sushko (2022)). When dealer capital deteriorates, accommodating demand from leveraged clients requires greater price concessions. Non-financial clients, such as corporates, trade for different reasons and provide dollar liquidity to the market (Cerrato et al. (2011); Menkhoff et al. (2012); Burnside et al. (2025a)). This capital-dependent demand amplifies the supply-side effect. It interacts with the steepened supply curve to generate larger price impact during stress.

Our mechanism does not exclude asymmetric information. Asymmetric information may also contribute to the predictive content of FX volume. However, demand-based models resting on asymmetric information alone cannot explain why volume predictability is absent before 2008. They also cannot explain why it emerges only in periods of severe balance-sheet stress. A supply-side channel is needed to rationalise these patterns.

The empirical results in recent papers are consistent with our argument. Huang et al. (2025) show that the FX liquidity supply curve is steeper when dealers are constrained. Ferreira et al. (2024) show that central bank FX interventions have a stronger impact when dealer balance sheets are constrained and dollar liquidity is scarce. Our paper builds on these findings but focuses on a different mechanism. We emphasise equity-holder incentives and debt overhang costs rather than regulatory constraints or generic funding stress. In the empirical analysis, we distinguish our mechanism from generic funding stress by exploiting variation in dealer CDS spreads and the timing of balance-sheet shocks.

5.2.4 *Testable Predictions*

The framework above generates three sets of predictions that we test in the remainder of this paper.

Prediction 1: Supply curve steepening. The slope of the dollar supply curve should increase with dealer balance-sheet stress. We measure the slope as the price impact per unit of volume. We proxy balance-sheet stress using CDS spreads and leverage. We test this prediction in Section 5.3.2 using interaction regressions and rolling-window estimates.

Prediction 2: State-dependent price response. FX prices should respond sharply to trading pressure only when balance-sheet constraint and volume are jointly high. There should be no comparable response outside this joint state. We test this prediction in Section 5.4 using event-time regressions around CDS shocks.

Prediction 3: Capital-dependent demand. Dollar demand from leveraged clients should be sensitive to dealer capital conditions. Non-financial client flows should not be sensitive. This asymmetry amplifies the supply-side effect. We test this prediction in Section 5.5 using disaggregated order flow data.

We formalise these predictions in Section 5.6. There we develop a model of FX spot intermediation with debt overhang and capital-dependent demand.

5.3 Supply Curve Evidence

5.3.1 Data

We use two unqiue (bilateral) datasets from two large FX dealers. The first dataset uses 11 currencies against the US dollar (USD). The currencies include Euro(EUR), Japanese yen (JPY), British pound (GBP), Swiss franc (CHF), Australian dollar (AUD), New Zealand dollar (NZD), Canadian dollar (CAD), Mexican peso (MXN), South African rand (ZAR), Singapore dollar (SGD), and Hong Kong dollar (HKD). This dataset contains only seven G10 currencies (EUR, JPY, GBP, CHF, AUD, NZD, and CAD). For each currency pair, we have FX US$ trading volume from the first week of November 2002 to the fourth week of March 2012. Data is reported in Table 5.1 (A). We also have matching order flows for the same currencies, which have been kindly provided by Burnside et al. (2025a).

The second dataset consists of daily US$ equivalent volume across the G9 currencies. We have volume data for the Australian dollar (AUD), Canadian dollar (CAD), Euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), British Pound (GBP), Swedish krona (SEK), and Swiss franc (CHF). This measures the average daily volume based on client trades over the last 20 days, normalised by the 6-month median volume of those trades. The volume indicators are based on the total buy and sell trades of a currency by client type and are aggregated in USD equivalent terms regardless of the cross in which they are transacted. These are calculated separately for financial and non-financial clients. A value greater than one indicates median volume higher in the last 6 months. The data spans the period 2018 to 2021 at daily frequency. Data is reported in Table 5.1 (B). We also have, for the same dealer, order flows for the same currencies spanning the same period.

This chapter also shows the summary of CDS and Market Leverage in Table 5.3. Debt overhang arises when highly leveraged intermediaries face an increase in the cost of balance-sheet expansion. This is because part of the marginal surplus belongs to existing creditors. We use dealer credit default swap (CDS) spreads and market leverage to measure this cost. CDS spreads capture the market-implied cost of creditor claims, while higher leverage increases the wealth transfer from equity to debt when the balance sheet expands.

5.3.2 Core Empirical Results

In this part, we want to show some evidence for the slope of the supply curve steepening. CDS shocks align timing of stress. CDS level identifies tight balance sheets. Volume identifies forced trading. Interaction identifies state-dependent price impact. Large price responses occur only when both constraints and volume are high. The strategy identifies whether trading volume influences prices only when intermediary capacity is constrained. This is also consistent with fire-sale dynamics and liquidity spiral models. The interaction coefficient is interpreted as the state-dependent slope of the FX dollar supply curve.

We first do the regression according to the equation (5.1), where we use the coefficient of $normalizedvolume \times CDS$ as the slope of the supply curve.

$$P_t = a + b_0 nv_t + b_1(nv_t \times CDS_t) + \epsilon \tag{5.1}$$

where P_t is the exchange rate return, $a$is the intercept, ϵ is the error term and $nv_t$is the normalized volume at time t.

Table 5.4 shows the results for equation (5.1). Panel A shows the results for the whole COVID-19 sample period, which is from 2018 to 2021. Panel B shows the period that focuses on before the quantitative easing, and Panel C shows the period after it. Here we separate our sample into two period which aims to cancel the effect that comes from the quantitative easing. In Panel D, we show the results before the financial crisis, which is from November 2002 to 2007. Here we want to use the period without a big shock to see how the slope of the supply curve will change. And we can clearly see that in panel B, our results show positive and significant results, and in panel D, results become negative and insignificant. These results are consistent with our Figure (5.9) and the opinion we mentioned in the former section: during the normal period, the supply curve does not have too much change, and during the shocks, the slope of the supply curve increases.

For enhancing our viewpoint, we also do the rolling regression for equation (5.1), and test that the covariance $Cov(CDS * Vol, b_1)$. If the covariance is larger than zero, the slope increases. We shows the results in Table 5.5. We can see that we get the same results as in Table 5.4, when during the shock, which is during the Covid-19 period and before the quantitative easing, the covariance is positive, which means the slope of the supply curve increases.

In order to emphasise our results, this paper also generates the Market Leverage by using 12 banks' market leverage and book debt (equation (5.2)) and does the regression between exchange rate return and Normalised volume $\times$ Market Leverage.

Furthermore, we still do the rolling regression on equation (5.3) and then calculate the covariance between Normalized volume $\times$ Market Leverage and b_1 in equation (5.3). We get similar results as when we use the CDS, when during the shock period, the slope of the supply curve increases.

$$MarketLeverage_t = (MarketEquity_t + BookDebt_t)/MarketEquity_t \tag{5.2}$$

$$P_t = a + b_0 nv_t + b_1(nv_t \times MarketLeverage_t) + \epsilon \tag{5.3}$$

After we get the results above, we further separate our sample to two groups according to the medium of CDS / Market Leverage, and redo the equation (5.1) and (5.3), and we get the results in Table 5.8 and 5.9. We can see when CDS / Market Leverage is high, the b_1 is positive and significant. This result is consistent with our view: during the shock period, when debt overhang is high, the slope of the supply curve increases.

In this part, we further use equation 5.4 to estimate the key parameters, and thereafter equation 5.5 and CDS spreads data, to estimate the slope of the supply curve. Finally, we plot the results of the margin effect in Figure 5.1, 5.2, and 5.3. On the y-axis, we show the price impact per unit of volume (the supply-curve slope). Unlike before, here the analysis shows the same mechanism but in averages, not around events as above.

In Figure 5.1, we use the volume sample over the 2008 Global Financial Crisis. FX trading volume here is aggregate dealer FX volume (no client breakdown). During the 2008 crisis (but also during the 2011-2012 euro-area sovereign debt crisis), FX volume had a much larger price impact when dealer balance-sheet stress (CDS) was higher.

Figures 5.2 and 5.3 show that during periods of very high dealer CDS, such as the COVID episode, FX trading volume from both leveraged and non-leveraged clients is associated with similarly large price impacts.

$$r_{it} = \beta_1 r_{i,t-1} + \beta_2 nv_{i,t-1} + \beta_3 \left(nv_{i,t-1} \times CDS_{i,t-1}\right) + \boldsymbol{\delta}' Control_{it} + \gamma_c + \varepsilon_{it} \tag{5.4}$$

$$\frac{\partial r_{it}}{\partial nv_{i,t-1}} = \beta_2 + \beta_3\, CDS_{i,t-1} \tag{5.5}$$

5.4 Mechanism and Identification: Supply Curve Steepening

The results so far show that FX spot dollar volume predicts exchange rate movements only when dealer balance sheets are impaired. While this evidence is consistent with a supply-side mechanism, it does not by itself distinguish between alternative channels through which balance-sheet stress could affect prices. In this section, we provide direct evidence on the mechanism underlying our main findings and clarify the source of identification. We show that the predictive content of FX volume arises from equity-holder pricing incentives associated with debt overhang. Empirically, that means that the same quantity pressure (high volume) moves prices more precisely around constraint shocks (large Δ CDS) and especially in the joint state (high constraints $\times$ high demand/pressure). This is the mechanism driving our empirical results and illustrated by our theoretical model.

We use changes in dealer CDS spreads to identify shocks to balance-sheet tightness that are plausibly exogenous to contemporaneous FX volume. CDS spreads reflect the market valuation of the intermediary's default risk and funding costs, and therefore the severity of debt overhang borne by equity holders (see Andersen et al. (2019); Cerrato and Mei (2025)). Unlike measures of trading activity or volatility, CDS spreads respond directly to changes in the relative claims of creditors and equity, making them a theoretically motivated proxy for the private marginal cost of balance-sheet expansion.

We define CDS change:

$$\Delta CDS_{i,t} = CDS_{i,t} - CDS_{i,t-1}. \tag{5.6}$$

We use CDS spreads to capture shocks to dealer balance-sheet tightness. We interpret changes in CDS spreads larger than 90th percentile as an unexpected worsening in the dealer's effective marginal cost of balance-sheet expansion. This is the timing ingredient for the event study in this section.

We introduce a stress event indicator:

$$Shock_{i,t} = \mathbf{1}\big(\Delta CDS_{i,t} \geq Q90\big(\Delta CDS_i\big)\big)\ , \tag{5.7}$$

The indicator focuses on extreme tightenings where steepening should be most visible.

Second Step: We define the joint state. Joint equals 1 when both the balance sheet constraint (in our case, debt overhang) and trading pressure are high:

$$Constraint_{i,t} = \mathbf{1}(CDS_{i,t} \geq Q50(CDS_i)) \tag{5.8}$$

The shock date tells us when something happened, but the steepness depends on how tight conditions are. The supply curve is expected to be steeper when constraints are high, not necessarily whenever there's a one-off change.

$$Demand_{i,t} = \mathbf{1}(Volume_{i,t} \geq Q75(Volume_i)) \tag{5.9}$$

This captures periods when fx dollar demand is significantly high.

$$Joint_{i,t} = Constraint_{i,t} \times Demand_{i,t} \tag{5.10}$$

Finally, in line with our earlier empirical results, we define the joint-state.

To make dynamic price adjustments around stress events visible, we estimate stacked event-time regressions. Let e index events and τ time (in days or weeks) around stress events.

Define a time dummy:

$$D_\tau = \mathbf{1}(t - t_e = \tau) \tag{5.11}$$

Equation (5.12) compares how prices behave around balance-sheet stress events. We first identify moments when dealer balance-sheet conditions suddenly worsen (large CDS increases). Around each such moment, we line up returns in event time. Then we split observations into two groups: (i) periods when trading pressure is high, and balance sheets are already tight, and (ii) all other periods. Equation (5.12) estimates two average return paths around the same type of shock, one for each group, while absorbing any shock-specific or currency-specific effects. If the FX supply curve steepens under balance-sheet stress, prices should move more after the shock only in the first group. That difference in post-shock behaviour is evidence for supply-curve steepening. This event study will help us to identify that when the marginal cost of expanding dealer balance sheets rises, dealer CDS spread rises, which is consistent with our debt overhang mechanism and our model.

$$r_{i,e,\tau} = \sum_{\tau \neq -1} \beta_\tau^{Joint} D_\tau \times Joint_{i,e} + \sum_{\tau \neq -1} \beta_\tau^{Other} D_\tau \times (1 - Joint_{i,e}) + \alpha_i + \delta_e + \varepsilon_{i,e,\tau}. \tag{5.12}$$

Where:

- $\tau = -1$ is omitted as the reference pre-event period;
- α_i are currency fixed effects;
- δ_e are event fixed effects.

Figure 5.4 and Figure 5.5 plot FX returns in event time around large CDS increases (balance-sheet stress shocks), separately for High CDS $\times$ High Volume (joint state), and all other states. Therefore results show that prices move more only after stress shocks are combined with higher volumes. The results show that there are no pre-trends in either group, and we observe a sharp and economically large post-event price response only in the joint state. Little or no response outside the joint state. This figure provides direct dynamic evidence of supply-curve steepening. Prices move only when balance-sheet stress coincides with strong quantity pressure. This is exactly what a steep supply curve implies: prices respond strongly to quantities only when the marginal cost of intermediation is high. Crucially, the absence of pre-trends rules out anticipation, gradual information diffusion, or slow-moving risk premia.

Figure 5.4 shows that supply-curve steepening bites when trading pressure is high during COVID. Evidence on the composition of that pressure is provided in Figures 5.10 and 5.11 in Appendix 5A.1.

Figure 5.5 shows that non-leveraged client volume is also associated with price responses during COVID stress events, though differences in persistence become clearer in online-Appendix Figures 5.10 and 5.11

Finally, while Figures 5.4 and 5.5 show that high trading pressure during COVID balance-sheet stress is associated with FX price responses for both client types, Figures 5.10 and 5.11 in Appendix 5A.1 reveal that these responses are more persistent and economically larger when trading pressure originates from leveraged clients.

Figure 5.12 in the online Appendix shows the results during the 2008 financial crisis. These are in line with what we have already discussed regarding the COVID-19 period. Figure 5.13 reports a placebo test using data between 2003-2007. Clearly, the strong empirical evidence reported for the 2008 financial crisis and the COVID-19 shock disappears.

5.5 Demand for US Dollars

In this section we focus now on the demand side and consider the interplay between the supply friction discussed earlier and the demand for dollars. This interplay is key to explain the positive estimated (interaction) coefficient on FX volume. This is also in line with the results reported in the previous section.

To dive deeper into this, we present three distinct event studies in the online Appendix 5C. Two of them relate to the two shocks we study in this paper (2008 financial crisis in panel b and COVID-19 in panel c), while the third one relates to the 2003 oil shock, panel a. Clearly post-2008 there is a positive and strong correlation between surge in FX volume and balance sheet constraints as proxied by the 5 year CDS of the largest 6 US and 6 European banks. Therefore, following the shock, FX volume surges and the dealer balance sheet constraint tightens. In this situation, the dollar appreciates.

Before 2008, the correlation between FX volume and dealers' balance sheet constraints flips in sign, becoming negative. This result, together with the evidence from Figure 4.3 and Figure 4.4, would suggest that before 2008, the dealer could accommodate the surge in demand with less impact on price.

As suggested by our model, leveraged customers prefer trading with dealers whose capital is higher (debt overhang is lower), while flows from non-financial customers are not related to the capital of the dealer. There is abundant literature in FX microstructure showing that non-financial customers trade with the dealers for different reasons, and they provide dollar liquidity to the market (Cerrato et al. (2011); Menkhoff et al. (2016); Burnside et al. (2025a)).

In the rest of this section, we dive deeper into the way the dealer and clients trade in the bilateral market, focusing on the demand side. In line with the evidence in the Online Appendix 5C, we now present evidence suggesting that during the period we study in this paper, the demand of US dollars has been also significantly higher. We focus on two large shocks (the 2008 financial crisis and COVID-19) covering our sample period. The combination of higher demand for dollars and constrained dealers would explain the empirical results in Table 4.7 and Table 4.9 (and consistent with Figure 5.9).

In Figure 5.6 (a,b) and Figure 5.7 (a,b), we plot the cumulative (aggregate and disaggregate) order flows of the two dealers. Negative flows suggest a greater demand for dollar liquidity. Clearly, there is a significant demand for dollars. The increase in demand for the dollar arises mainly from financials, while non-financials (especially during COVID-19) take the opposite side. Given that the dealer is balance sheet constrained (supply-side constraints), she will have to trade with clients in a way that attracts foreign flows to match dollar ones.

Du et al. (2018b), and other recent papers (see, for example, Krohn and Sushko (2022)) show an increasing trading competition amongst G-SIB dealers in the spot market after 2008. This evidence is in line with other markets, such as the Treasury market (Duffie (2010)). Leveraged clients prefer to trade with dealers with lower debt overhang costs (i.e. lower funding costs in our case), as they can obtain better quotes from these dealers.

Based on recent empirical evidence (for example Du et al. (2018b)), we conjecture (and our model explains this) that the dealer's capital plays an important role (amongst other things) for the dollar market. Dealers with higher levels of capital (or lower leverage) are better positioned to match their clients' dollar demand. We do not have data for a large panel of dealers and, therefore, cannot study how (in the cross-section) capital is related to the demand for dollars from clients. This is what our model would suggest. However, we can still study the time series effect of dollar flows from clients and dealer leverage (or capital).

We do this in Table 5.12. We study whether changes in the dealer's capital can predict changes in her own dollar flows. We focus on the second dealer as it is only with Basel III that banks have started optimising capital across trading desks, and business competition amongst FX dealers has become tighter. In Table 5.12, we use quarterly data as we wish to match the flows of our dealer with its balance sheet data. We do not have daily balance sheet data for this dealer. We collect balance sheet data for our second dealer from Bloomberg and construct the He et al. (2017) measure of leverage to match the flows data of this dealer.

Table 5.12 shows the empirical results. Results in (1)-(3) refer to the flows across different segments (aggregate, Financial, Non-Financial). Leverage refers to the leverage of the second dealer. In line with our model, we focus on lagged leverage (predictability). We run a time series regression of changes in flows (we sum up flows across all the G-9 currencies) on changes in lagged leverage. We include an intercept.

Results in Table 5.12 suggest that changes in leverage predict subsequent changes in dollar flows. Leveraged clients prefer trading with dealers whose capital is higher (debt overhang in lower). For example, note that the predictability of the leverage arises from financial clients, while it is insignificant for non-financials. This suggests that price-sensitive customers are important, as it is the demand for dollars arising from this segment that have a significant price impact on the dealer balance sheet.

The demand-side evidence in this section is in line with the earlier event studies showing that FX prices respond precisely during periods in which dollar demand, especially from financial clients, is elevated and balance-sheet stress is high, while no such responses appear when these demand patterns are absent.

5.6 Model: FX Spot Intermediation with Debt Overhang and Capital-Dependent Demand

Time is discrete. $t = 0, 1, 2.....$The dealer intermediates USD vs foreign currency spot trades across currency pairs indexed by $i \in 1, ..., N$. Let $P_{i,t}$ denote the USD price of one unit of foreign currency i at time t.

The dealer faces two frictions:

Equity holders maximise their own continuation value; they do not internalise creditor gains: when the dealer expands its gross balance sheet, part of the marginal surplus from intermediation accrues to existing creditors, so equity holders face a private marginal cost of balance-sheet expansion. This incentive distortion operates through pricing and is present even when balance-sheet constraints do not bind Andersen et al. (2019)). Therefore, the key friction in our model is not merely a binding balance-sheet constraint, but an incentive distortion faced by equity holders. When the dealer expands its balance sheet to intermediate FX trades, part of the resulting surplus accrues to existing creditors. Equity holders do not internalise these creditor gains and therefore require compensation to expand intermediation. This generates a debt-overhang wedge that directly affects quoted prices. It turns that, this wedge can be present even when regulatory or leverage constraints are slack, and should be interpreted as a pricing distortion rather than a hard constraint on quantities

Second, client-side market frictions on the demand side: the mass of price-sensitive clients reaching the dealer depends on the dealer's capital position, reflecting slow-moving capital and OTC competition (Duffie (2010)).

We model the dealer as the marginal price setter in a bilateral OTC market.

Demand Side

Let per-client demand for USD liquidity in currency i be $d_{i,t}(P_{i,t})$, with

$$\frac{\partial d_{i,t}(P_{i,t})}{\partial P_{i,t}} < 0 \tag{5.13}$$

higher USD price (a worse quote for the client) reduces the demanded quantity.

Let the mass of price-sensitive clients reaching the dealer be $m_{i,t}(K_{t-1})$, with

$$\frac{\partial m_{i,t}(K_{t-1})}{\partial K_{t-1}} > 0 \tag{5.14}$$

better-capitalized dealers offer better expected execution or quotes and therefore attract more client flow (tight OTC competition; Duffie slow-moving capital).

Total dealer demand is

$$D_{i,t}(P_{i,t}, K_{t-1}) = m_{i,t}(K_{t-1})\, d_{i,t}(P_{i,t}) \tag{5.15}$$

and thus

$$\frac{\partial D_{i,t}}{\partial P_{i,t}} < 0, \qquad \frac{\partial D_{i,t}}{\partial K_{t-1}} > 0 \tag{5.16}$$

Supply Side

Let $X_{i,t}$ denote the gross amount of intermediation in currency i (in foreign currency units), so the USD notional is $P_{i,t}X_{i,t}$. Intermediation expands gross assets and gross liabilities even if the dealer "matches" economically (net risk may be small, but the gross balance sheet still grows).

Write the dealer's gross assets as

$$A_t = R_t^A A_{t-1} + \sum_{i=1}^{N} P_{i,t} X_{i,t}, \tag{5.17}$$

and gross liabilities as

$$L_t = R_t^L L_{t-1} + \sum_{i=1}^{N} F_t X_{i,t} \tag{5.18}$$

F_t is the USD funding needed per unit of $X_{i,t}$. $P_{i,t}X_{i,t}$ is the dealer's USD asset exposure created by buying or selling foreign currency; $F_t X_{i,t}$ is the associated funding requirement on the liability side.

Define equity capital as

$$K_t \equiv A_t - L_t \tag{5.19}$$

A minimal leverage (balance-sheet) constraint is

$$K_t \geq \underline{K}_t \tag{5.20}$$

where $\underline{K}_t$ can be interpreted as a minimum equity buffer. This follows the logic of predetermined capital as in Admati et al. (2018).

$\underline{K}_t$ can also be interpreted as the inelastic USD supply constraint. After a negative shock, K_{t-1} falls closer to $\underline{K}_t$, making the constraint bind more often.

It is useful to distinguish this feasibility constraint from the mechanism that drives pricing in the model. The constraint above limits how far the dealer can expand its balance sheet, as in standard balance-sheet-constraint models. By contrast, debt overhang operates through equity-holder incentives: when equity is scarce, expanding intermediation transfers value to creditors, so equity requires compensation and adjusts prices accordingly. As a result, balance-sheet constraints determine whether intermediation is feasible, while debt overhang determines how intermediation is priced.

We now define an endogenous shadow funding wedge that captures the equity-holder cost of expanding the balance sheet when the dealer is levered.

Let the dealer face an effective equity-holder funding cost:

$$\widetilde{F}_t = F_t + \phi_t, \tag{5.21}$$

where $\phi_t \geq 0$ is the debt-overhang wedge: the private marginal cost (for equity) of raising one more unit of funding.

When new funding is raised, part of the benefit accrues to existing creditors, so equity requires compensation. This reduces the equity-relevant margin. affecting the price even when the shadow cost of capital is zero. This is explicitly motivated by creditor wealth transfers (Andersen et al. (2019)).

Now impose that ϕ_t is increasing as equity becomes scarce (high leverage / low K):

$$\phi_t = \phi\left(\frac{L_t}{A_t}, K_t\right), \qquad \frac{\partial \phi}{\partial (L/A)} > 0, \qquad \frac{\partial \phi}{\partial K} < 0 \tag{5.22}$$

when leverage is higher (or capital lower), debt overhang is more severe, and the wedge is larger. This corresponds to the common implication of Admati and Andersen: equity scarcity creates a private wedge. Empirically, we approximate this using leverage, CDS spreads, or LIBOR–OIS.

Using (5.17)–(5.18) and (5.19), capital evolves as

$$K_t = R_t^A A_{t-1} - R_t^L L_{t-1} + \sum_{i=1}^{N} \big(P_{i,t} - F_t\big) X_{i,t} \tag{5.23}$$

Alternatively, if one wishes to embed the debt-overhang wedge directly into capital accumulation from an equity perspective, we can replace F_t with $\widetilde{F}_t$:

$$K_t = R_t^A A_{t-1} - R_t^L L_{t-1} + \sum_{i=1}^{N} \big(P_{i,t} - \widetilde{F}_t\big) X_{i,t} \tag{5.24}$$

The term $\big(P_{i,t} - \widetilde{F}_t\big) X_{i,t}$ is the equity-relevant intermediation margin. When ϕ_t rises, the effective margin shrinks, making USD provision “more expensive” in equilibrium.

Define period-t intermediation profit as

$$\pi_t \equiv \sum_{i=1}^{N} \big(P_{i,t} - F_t\big) X_{i,t} \tag{5.25}$$

Alternatively, one can also consider profits net of the debt-overhang wedge (equity valuation relevant):

$$\pi_t^E \equiv \sum_{i=1}^{N} \big(P_{i,t} - \widetilde{F}_t\big) X_{i,t} = \pi_t - \phi_t \sum_{i=1}^{N} X_{i,t} \tag{5.26}$$

ϕ_t is the private shadow cost (FVA-like) that equity requires to expand gross intermediation.

The dealer maximises equity value:

$$J_t = \pi_t^E + \mathbb{E}_t[M_{t+1} J_{t+1}]\,, \tag{5.27}$$

where M_{t+1} is a stochastic discount factor (SDF).

Equitmediation.

The dealer sets quotes $P_{i,t}$. Client demand determines quantities:

$$X_{i,t} = D_{i,t}(P_{i,t}, K_{t-1}) \tag{5.28}$$

The dealer is choosing price; quantity is the demand response. This makes the model directly interpretable as a supply curve (price as a function of quantity pressure).

The dealer also must satisfy the capital constraint (5.20), where K_t depends on $\{P_{i,t}, X_{i,t}\}$ through (5.24).

The dealer chooses $\{P_{i,t}\}_{i=1}^N$ to maximize (5.27) subject to (5.28) and the capital constraint (5.20), with capital given by (5.24).

The period-t Lagrangian is:

$$\mathcal{L}_t = \pi_t^E + \mathbb{E}_t[M_{t+1} J_{t+1}] + \lambda_t\big(K_t - \underline{K}_t\big), \qquad \lambda_t \geq 0 \tag{5.29}$$

λ_t is the tightness of the balance-sheet constraint. When $\lambda_t > 0$, the dealer prices with a binding scarcity of capital.

After differentiating with respect to $P_{i,t}$, and using that $X_{i,t} = D_{i,t}(P_{i,t}, K_{t-1})$, so

$$\frac{\partial X_{i,t}}{\partial P_{i,t}} = \frac{\partial D_{i,t}}{\partial P_{i,t}} < 0, \tag{5.30}$$

the first-order condition with respect to $P_{i,t}$ is

$$\frac{\partial \mathcal{L}_t}{\partial P_{i,t}} = \frac{\partial \pi_t^E}{\partial P_{i,t}} + \frac{\partial}{\partial P_{i,t}} \mathbb{E}_t[M_{t+1} J_{t+1}] + \lambda_t \frac{\partial K_t}{\partial P_{i,t}} = 0 \tag{5.31}$$

Using now the continuation-value part in the Lagrangian, and noting that the continuation value depends on today's capital, the chain rule implies

$$\frac{\partial}{\partial P_{i,t}} \mathbb{E}_t[M_{t+1} J_{t+1}] = \mathbb{E}_t\left[M_{t+1} \frac{\partial J_{t+1}}{\partial K_t}\right] \frac{\partial K_t}{\partial P_{i,t}} \tag{5.32}$$

Plugging (5.32) into (5.31) yields

$$\frac{\partial \pi_t^E}{\partial P_{i,t}} + \left(\lambda_t + \mathbb{E}_t\left[M_{t+1} \frac{\partial J_{t+1}}{\partial K_t}\right]\right) \frac{\partial K_t}{\partial P_{i,t}} = 0 \tag{5.33}$$

Define the effective shadow value of capital as

$$\bar{\lambda}_t \equiv \lambda_t + \mathbb{E}_t\left[M_{t+1} \frac{\partial J_{t+1}}{\partial K_t}\right] \tag{5.34}$$

Even if the contemporaneous constraint is slack ($\lambda_t = 0$), equity may still value capital because it relaxes future distortions (under-intermediation). This is also in line with Admati et al. (2018)Admati et al (2018). Thus, $\bar{\lambda}_t$ is forward-looking. It reflects equity scarcity and could also exist even without creditor-equity conflict. The shadow value of intermediary capital arises as a state variable because capital is scarce relative to risk-bearing needs (He et al. (2022)). In this paper, we interpret it also as a measure which captures the marginal value of balance-sheet capacity from the perspective of equity holders, incorporating both current funding conditions and anticipated future constraints. In this sense, the shadow cost, in our case, reflects an intertemporal debt-overhang cost: expanding intermediation today reduces the equity value of future opportunities by tightening expected balance-sheet conditions. This forward-looking incentive channel is important for our interpretation.

After solving for the shadow cost, rearranging (5.33) gives

$$\bar{\lambda}_t = -\frac{\dfrac{\partial \pi_t^E}{\partial P_{i,t}}}{\dfrac{\partial K_t}{\partial P_{i,t}}} \tag{5.35}$$

This is your shadow-cost formula.

To connect our empirical price impact per unit volume, we want the relation between the chosen quote $P_{i,t}$ and quantity $X_{i,t}$. Using $X_{i,t} = D_{i,t}(P_{i,t}, K_{t-1})$, and inverting locally,

$$P_{i,t} = S_{i,t}\big(X_{i,t}; K_{t-1}, \phi_t, \bar{\lambda}_t\big)\,, \tag{5.36}$$

where $S_{i,t}$ is the dealer's effective supply curve.

Note that

$$\frac{\partial P_{i,t}}{\partial X_{i,t}} \text{ increases when } \ \bar{\lambda}_t \text{ increases and/or } \ \phi_t \text{ increases} \tag{5.37}$$

When capital is scarce (high $\bar{\lambda}_t$) or when debt overhang is severe (high ϕ_t), the dealer requires a larger price concession per unit of intermediation, generating a steeper supply curve. Therefore, during stress, volume can rise while constraints tighten. Our model rationalises this through a combination of a higher debt-overhang wedge pushing prices up, a negative shock shifting $d_{i,t}(\cdot)$ and increasing quantities, and capital-dependent matching $m_{i,t}(K_{t-1})$, which can amplify reallocation across dealers.

Formally, a crisis demand shift can be represented as a parameter θ_t entering per-client demand:

$$d_{i,t}(P) = d_i(P; \theta_t)\,, \qquad \frac{\partial d_i}{\partial \theta_t} > 0 \tag{5.38}$$

Then, even if ϕ_t rises, $X_{i,t}$ can increase if θ_t rises sufficiently.

5.7 Discussion on the Model

This section discusses how the model helps interpret the empirical findings and clarifies its relationship to the balance-sheet literature, with particular emphasis on the distinction between balance-sheet tightness, the shadow cost of capital, and equity-holder debt overhang.

Large negative shocks such as the Global Financial Crisis and the COVID-19 episode substantially reduced dealer equity, pushing intermediaries into states of elevated leverage and capital scarcity. In the model, this state is summarised by a higher shadow value of capital, reflecting the increased value of balance-sheet capacity when equity is scarce. This captures the balance-sheet tightness emphasised in the existing literature and describes the state of the intermediary following adverse shocks.

Debt overhang then operates as the mechanism through which this state affects pricing. When equity is scarce, expanding the dealer's gross balance sheet transfers value to existing creditors, so equity holders internalise a private marginal cost of intermediation. This debt-overhang wedge enters directly into pricing decisions and steepens the dealer's supply curve for dollar liquidity. Importantly, this mechanism can operate even when minimum-capital constraints do not bind, implying that balance-sheet stress need not result in quantity rationing. Instead, intermediation can continue at higher prices, generating larger price impact and sharp exchange-rate movements.

This distinction helps reconcile our empirical findings with the balance-sheet literature. Standard balance-sheet-constraint models often predict reduced intermediation or market shutdowns when constraints tighten. In contrast, our model predicts continued trading accompanied by worse prices. This prediction aligns closely with the behaviour of FX markets during stress episodes, where trading volume remains elevated while dollar funding becomes increasingly expensive.

Figures 5.6 and 5.7 provide direct empirical support for the demand-side frictions embedded in the model. Following large shocks, demand for U.S. dollars rises sharply and remains elevated for several weeks, consistent with slow-moving, price-sensitive client demand in OTC markets. Moreover, the composition of flows differs across client types, indicating that dollar demand is concentrated among clients that are particularly sensitive to execution quality and dealer balance-sheet conditions. In the model, this capital-dependent demand interacts with the steepened supply curve generated by debt overhang, amplifying price impact and contributing to persistent exchange-rate dynamics.

Overall, the model clarifies how balance-sheet stress-summarised by the shadow cost of capital-translates into exchange-rate movements through an equity-holder debt-overhang pricing mechanism. By shifting attention from intermediation capacity to the pricing of liquidity when equity is scarce, the model complements the balance-sheet literature and provides a unified interpretation of both the supply- and demand-side dynamics observed in the data.

5.8 Conclusion

This paper identifies and explains a supply-demand mechanism. Through this mechanism, dealer balance-sheet frictions affect price formation in the FX spot market. We show that dealer balance-sheet constraints make the supply of dollar liquidity more inelastic. When debt overhang costs rise, the dollar supply curve steepens. The same trading pressure generates a substantially larger exchange-rate response. This mechanism operates through equity-holder incentives rather than quantity rationing. Constrained dealers continue to intermediate, but only at worse prices.

Crucially, the supply-side friction interacts with a demand-side channel. Surges in dollar demand during crises come mainly from leveraged financial clients whose trading is sensitive to dealer capital conditions. Non-financial clients take the opposite side. This capital-dependent demand amplifies the effect of supply-curve steepening. The combination of higher demand for dollars and constrained supply generates a larger price impact and explains the observed positive correlation between lagged FX volume and subsequent dollar appreciation during stress.

Our analysis does not rule out that leverage ratio requirements play some role. However, regulatory frictions alone cannot explain the patterns we document. Our evidence points to debt overhang costs as a more fundamental and persistent driver (Myers (1977); Andersen et al. (2019); Cerrato and Mei (2025)). These costs stem from higher funding costs and capital structure frictions that emerged in the post-2008 era (Berndt et al. (2024)).

More broadly, our findings suggest that FX markets become more fragile when dealer balance sheets are impaired by debt overhang. Volume shocks translate into disproportionately large price movements. This insight is relevant for understanding FX market stress during the financial crisis and COVID-19. It is also relevant for evaluating the effectiveness of central bank interventions when dollar liquidity is short (Ferreira et al. (2024)). Our model further implies that higher equity capital, while costly for shareholders in the short run, can enhance future profitability by easing intermediation constraints (Admati et al. (2012)).

Figure 5.1: 2008 - margin

Figure 5.1 shows the results of equations below by using the 2008 sample.

$$r_{it} = \beta_1 r_{i,t-1} + \beta_2 nv_{i,t-1} + \beta_3 \left(nv_{i,t-1} \times CDS_{i,t-1}\right) + \boldsymbol{\delta}' Control_{it} + \gamma_c + \varepsilon_{it} \tag{5.39}$$

$$\frac{\partial r_{it}}{\partial nv_{i,t-1}} = \beta_2 + \beta_3\, CDS_{i,t-1} \tag{5.40}$$

Here, we use the β_2 and β_3 values obtained in Table 5.10, along with the CDS data, to draw Figure 5.1.

Figure 5.2: 2020 - Leverage Volume -Slope

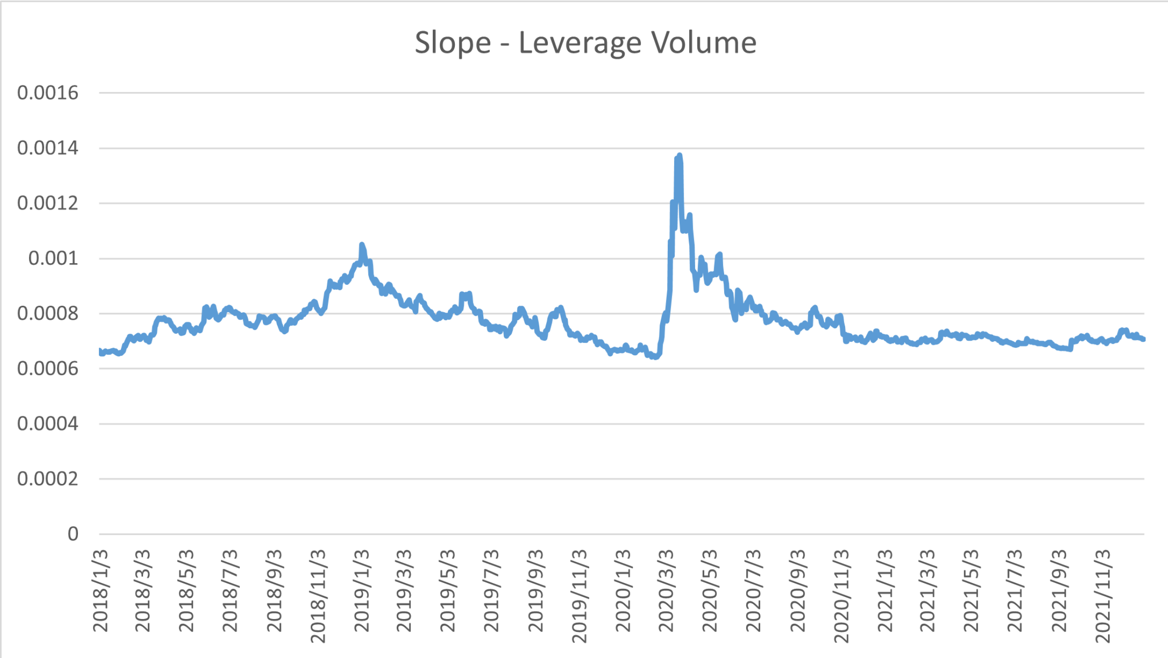


Figure 5.3: 2020 - Real Money - Slope

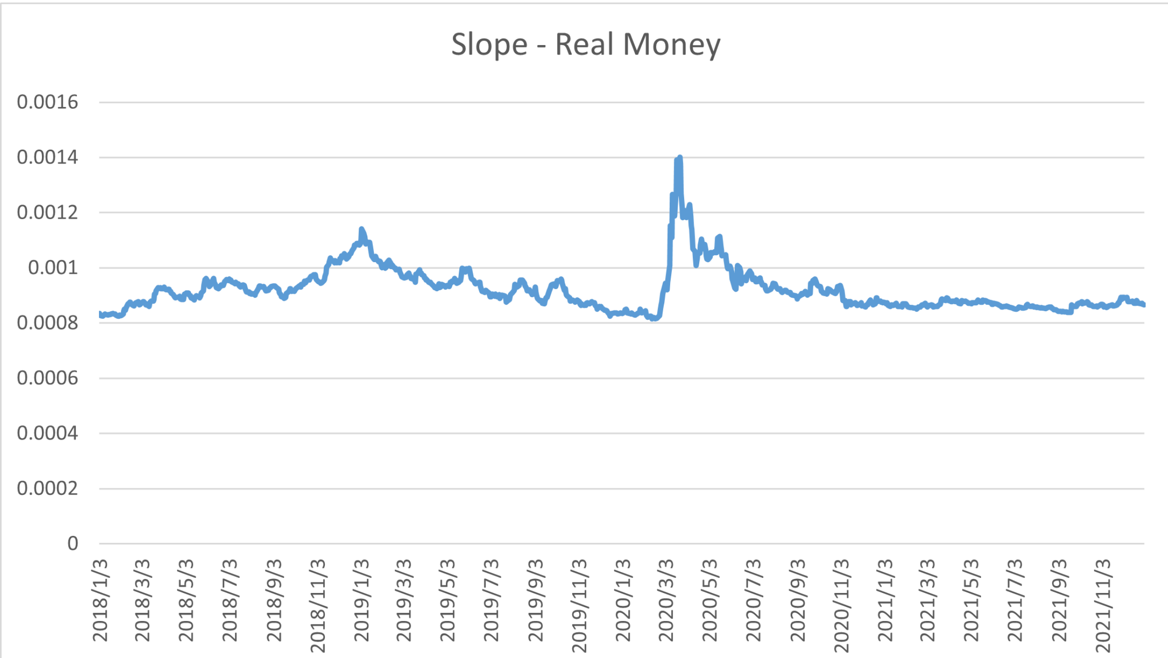


Figure 5.2 and 5.3 show the results of equations below by using the 2020 sample.

$$r_{it} = \beta_1 r_{i,t-1} + \beta_2 nv_{i,t-1} + \beta_3 \left(nv_{i,t-1} \times CDS_{i,t-1}\right) + \boldsymbol{\delta}' Control_{it} + \gamma_c + \varepsilon_{it} \tag{5.41}$$

$$\frac{\partial r_{it}}{\partial nv_{i,t-1}} = \beta_2 + \beta_3 \, CDS_{i,t-1} \tag{5.42}$$

Here, we use the β_2 and β_3 values obtained in Table 5.11, along with the CDS data, to draw Figure 5.2 and 5.3.

Figure 5.4: Event Study - 2020 - Leverage Volume

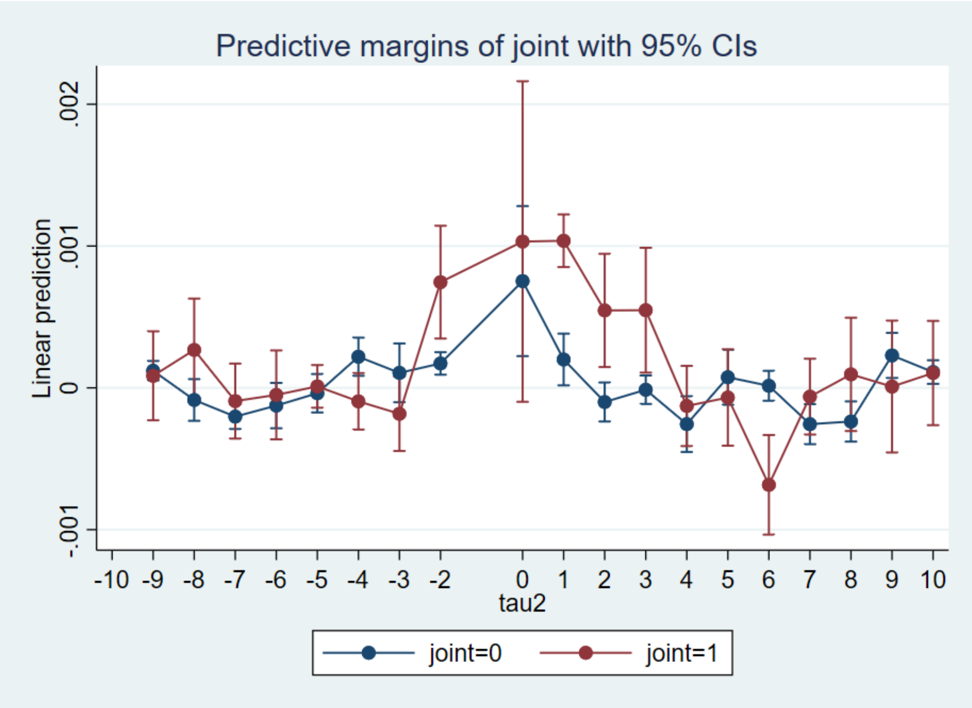


Figure 5.5: Event Study - 2020 - Real Money

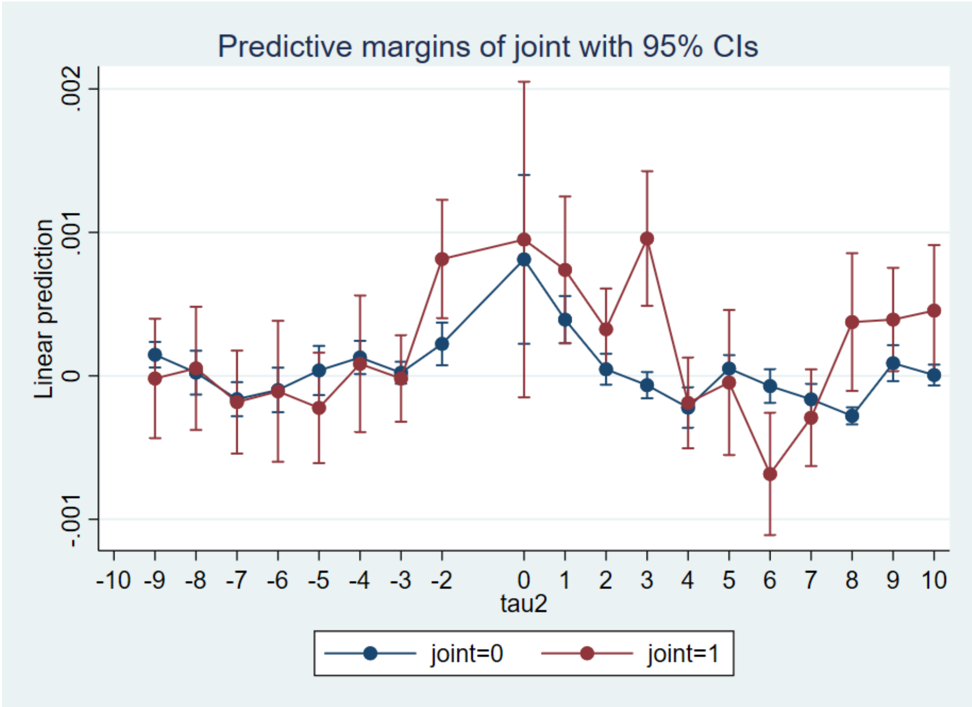


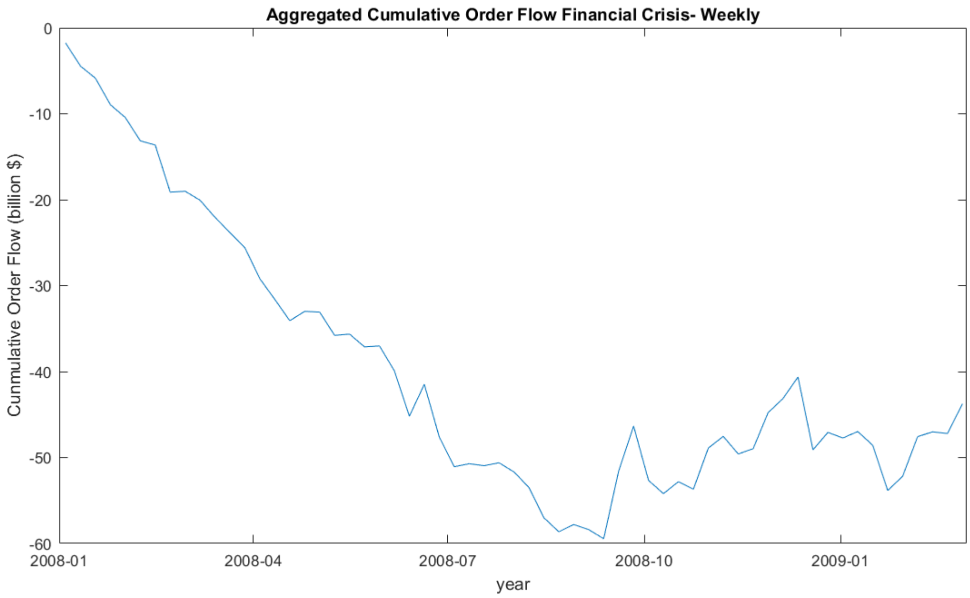
Figure 5.4 and 5.5 show the results of the equation below by using the sample from 2018 to 2021.

$$r_{i,e,\tau} = \sum_{\tau \neq -1} \beta_{\tau}^{Joint} D_{\tau} \times Joint_{i,e} + \sum_{\tau \neq -1} \beta_{\tau}^{Other} D_{\tau} \times (1 - Joint_{i,e}) + \alpha_i + \delta_e + \varepsilon_{i,e,\tau}. \tag{5.43}$$

Here red line shows the β_{τ}^{Joint}, which is the coefficient when both constraints and trading pressure are high. Blue line shows the β_{τ}^{Other}, in the opposite scenario.

Figure 5.6: Aggregated Cumulative Order Flow

(a) Financial Crisis - Weekly



(b) Covid 19 - Daily

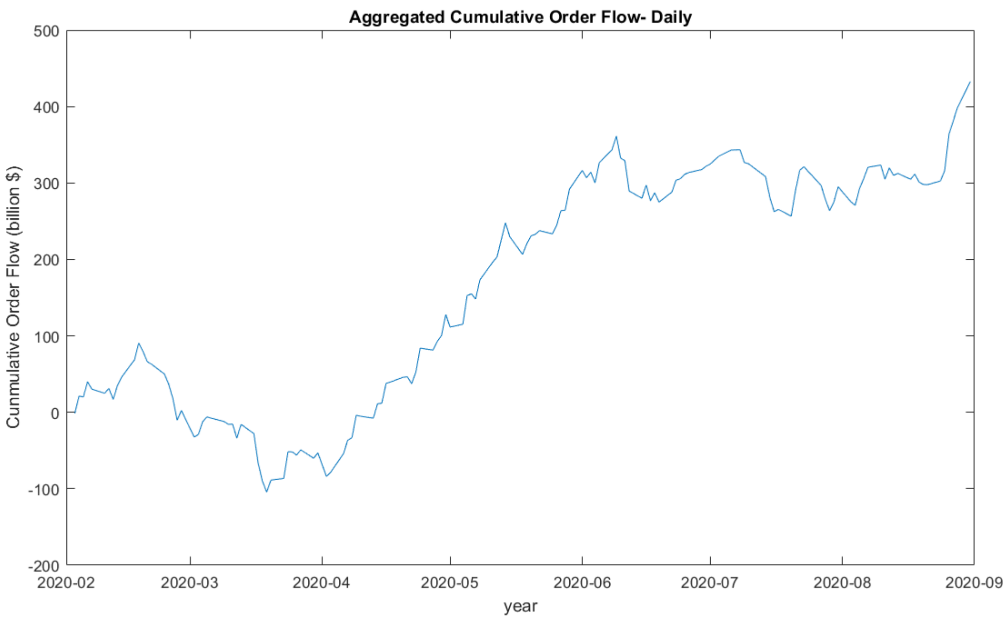
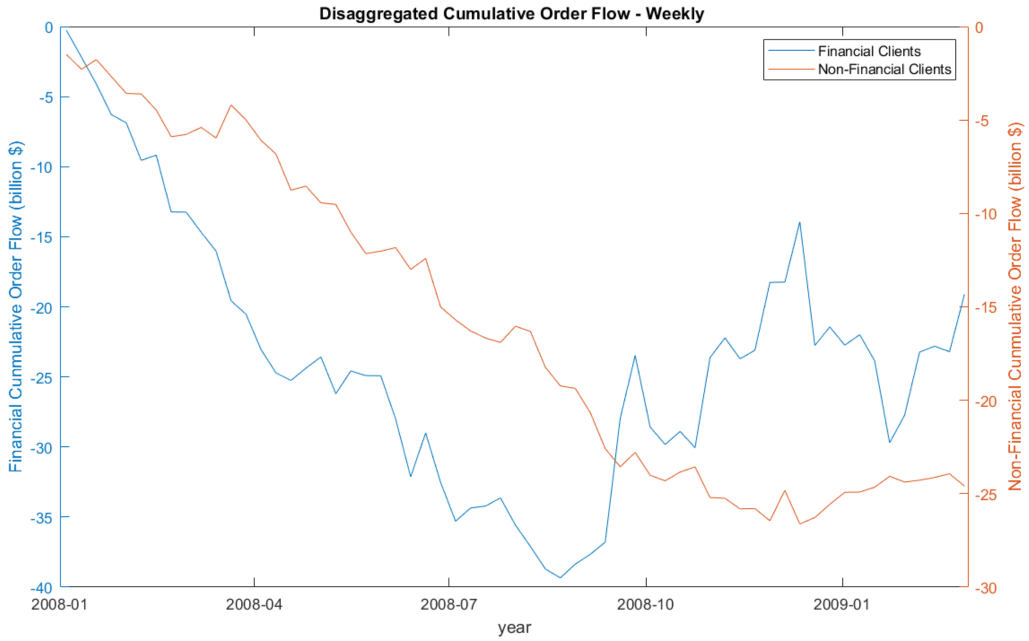


Figure 5.6 shows the aggregated cumulative order flow. We calculate it from January 2008 to March 2009 in (a). We show the cumulative flow from 2020 February to September. For our order flow data, negative suggests buying USD while positive is selling it.

Figure 5.7: Disaggregated Cumulative Order Flow

(a) Financial Crisis - Weekly



(b) Covid 19 - Daily

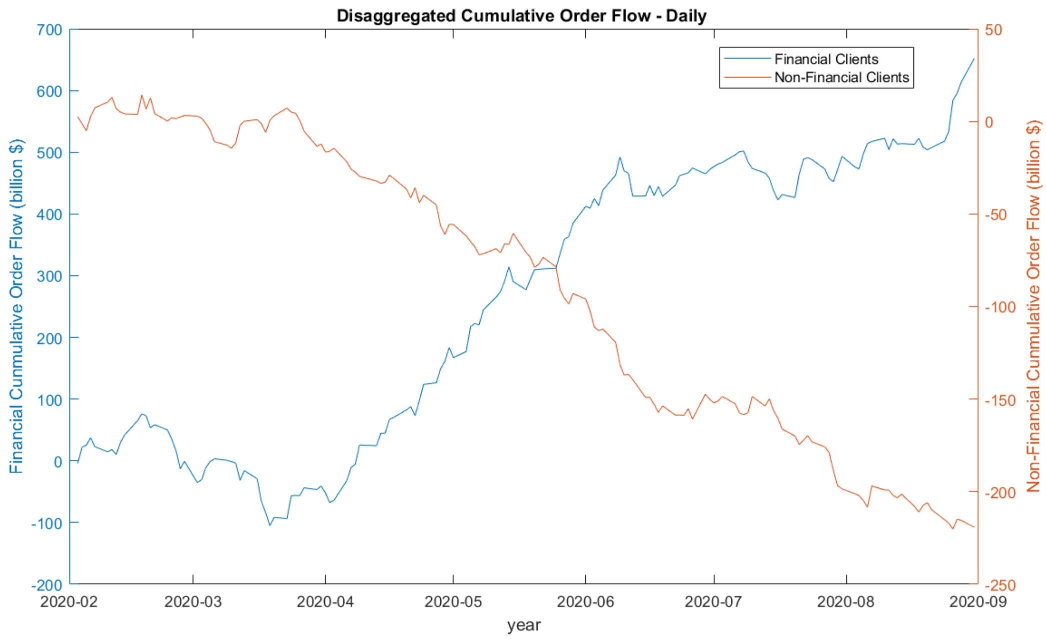
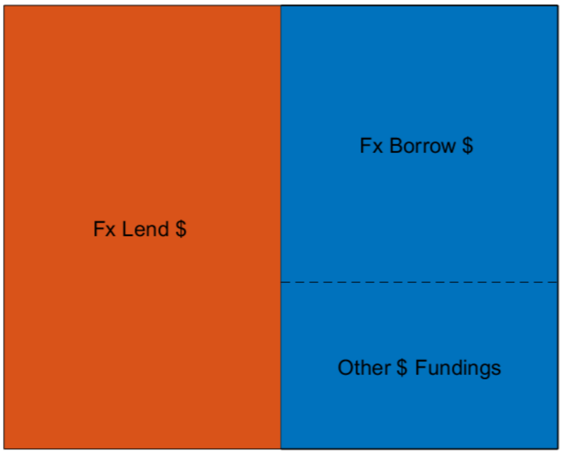


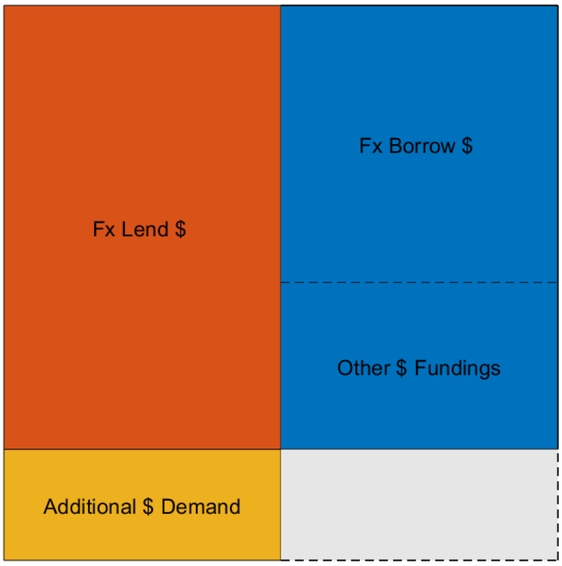
Figure 5.7 shows the disaggregated cumulative order flow. We use data from February 2020 to September.

Figure 5.8: Balance Sheet

(a) Normal Period



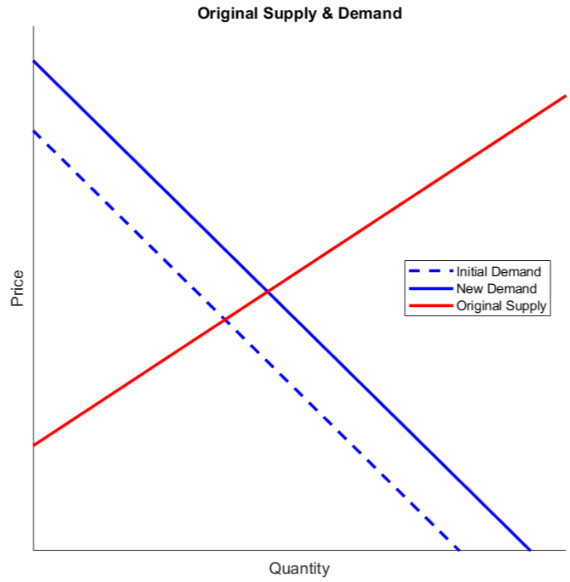
(b) During Shocks



We show the simplified balance sheet in Figure 5.8. We assume that the FX dealer has US$ lending on one side of the balance sheet and US$ borrowing on the other side. This could represent customers demanding and offering US$. Generally, the liability side will consist of liabilities financed externally (via US$ REPO market, for example or even commercial paper) or internally (generally uncollateralised borrowing via the Treasury).

Figure 5.9: Supply Demand Curve

(a) Normal Period



(b) During Shocks

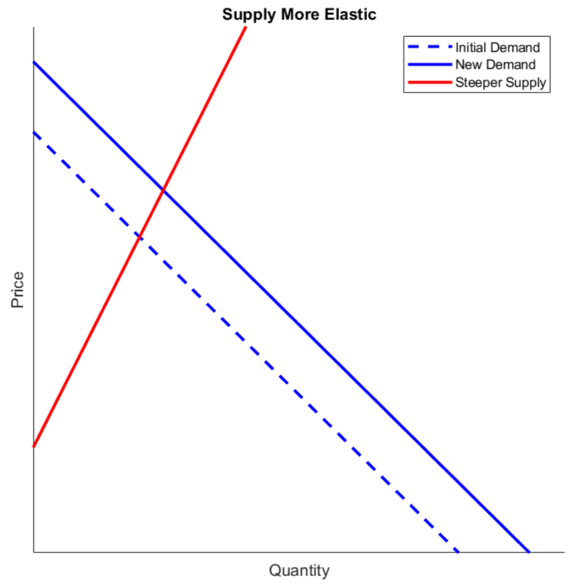


Figure 5.9 shows the supply-demand curve. In Figure 5.8 and 5.9, we show the normal period in Panel (a). And we suppose that following an exogenous shock, the equity capital of the dealer falls and, at the same time, the demand of US$ from clients surges (additional demand). The balance sheet of the dealer will show an imbalance between US$ demand from clients and the financing resources available (Figure 5.8 Panel b). To accommodate the demand, dealers will need to commit their own capital. However, generally, they are reluctant to do so to support the liquidity, particularly when their capital is already lower. This situation introduces debt overhang costs and it can drive the slope of the US dollar supply curve (see Figure 5.9 (a,b)).

Table 5.1: Summary of Volume

Panel A: First Dealer- Volume (billion$)					
Variables	N	Mean	S.D.	Min	Max
EUR	493	23.738	11.553	4.805	84.437
JPY	493	9.434	3.764	1.787	25.915
GBP	493	8.228	5.026	1.299	50.699
CHF	493	7.030	3.309	1.898	24.790
AUD	493	3.888	2.518	0.135	11.691
CAD	493	2.717	1.592	0.283	12.303
NZD	493	0.834	0.592	0.066	3.171
HKD	493	0.629	0.485	0.028	2.539
MXN	493	0.505	0.386	0.012	2.217
ZAR	493	0.491	0.424	0.010	2.395
SGD	493	0.455	0.333	0.015	1.790

Panel B: Second Dealer - Volume (billion$)					
Variables	N	Mean	S.D.	Min	Max
Leverage Volume	1,044	1.045	0.167	0.631	1.703
Real Money	1,044	1.112	0.137	0.650	1.626

Table 5.1 shows the summary of volume. This table shows the number of observations, mean, standard deviation, minimum value and maximum value of the volume. All the currencies in Table 5.1 use USD as the base currency. Panel A shows our first dealer and Panel B shows our second dealer.

Table 5.2: Summary Statistic - Order Flow

Order Flow -Second Dealer (billion$)					
Variables	N	Mean	S.D.	Min	Max
Aggregrated	1,044	-0.474	4.959	-15.022	17.557
Financial	1,044	0.029	5.059	-13.350	17.732
Non-Financial	1,044	-0.503	1.665	-5.856	4.909

Table 5.2 shows the summary of the order flow.

Table 5.3: Summary Statistic - CDS / Market Leverage

Panel A: CDS Spread (basis points)					
Variables	N	Mean	S.D.	Min	Max
CDS	1,044	56.108	14.556	36.591	146.441
Panel B: Market Leverage (basis points)					
Variables	N	Mean	S.D.	Min	Max
Market Leverage	1,044	9.967	2.826	6.387	18.076

Table 5.3 shows the summary of the debt overhang proxy.

Table 5.4: Slope Table

Panel A : Whole Period 2018-2021			
	(1) leverage volume	(2) real money	(3) total volume
b_1	0.0016**	0.0015**	0.0008**
	0.0007	*0.0007*	*0.0004*
$adj - R^2$	0.0247	0.0212	0.0242
Control	Yes	Yes	Yes
Nobs	1,044	1,044	1,044

Panel B: Before QE 2018-2020Mar			
	(1) leverage volume	(2) real money	(3) total volume
b_1	0.0023**	0.0022**	0.0011**
	0.0009	*0.0009*	*0.0005*
$adj - R^2$	0.0433	0.0379	0.0412
Control	Yes	Yes	Yes
Nobs	586	586	586

Panel C: After QE 2020Apr-2021			
	(1) leverage volume	(2) real money	(3) total volume
b_1	-0.0005	0.0002	0.0000
	0.0015	*0.0014*	*0.0007*
$adj - R^2$	0.0129	0.0115	0.0135
Control	Yes	Yes	Yes
Nobs	458	458	458

Panel D : Before Financial Crisis 2002Nov-2008	
	(1) aggregrate
b_1	-0.0017
	0.0022
$adj - R^2$	0.0041
Control	Yes
Nobs	265

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 5.4 shows the results for equation below.

$$P_t = a + b_0 nv_t + b_1(nv_t \times CDS_t) + \epsilon \tag{5.44}$$

where P_t is the exchange rate return, $a$is the intercept, ϵ is the error term and $nv_t$is the normalized volume at time t. Panel A shows the results for the whole Covid-19 sample period. Panel B and C show the period before and after quantitative easing; Panel D shows the period before the financial crisis.

Table 5.5: Covariance

	leverage volume	real money	total volume
Whole Period	-0.0638	-0.0418	-0.0263
Before QE	0.0755	0.1368	0.1056
After QE	-0.0501	-0.0712	-0.0514
	aggregrate		
Before Financial Crisis	0.0665		

In Table 5.5, we perform a rolling regression with a 20-day window on Equation (5.45).

$$P_t = a + b_0 nv_t + b_1(nv_t \times CDS_t) + \epsilon \tag{5.45}$$

Table 5.5 shows the covariance results between $CDS * NormalizedVolume$ and b_1 in Table 5.4. In this table, we show the same period as in Table 5.4, which is the whole COVID-19 period, before and after QE, and before the financial crisis.

Table 5.6: Slope Table - Market Leverage

Panel A : Whole Period 2018-2021			
	(1) leverage volume	(2) real money	(3) total volume
b_1	0.0000	0.0000	0.0000
	0.0025	*0.0025*	*0.0013*
$adj - R^2$	0.0118	0.0088	0.0117
Control	Yes	Yes	Yes
Nobs	1,044	1,044	1,044
Panel B: Before QE 2018-2020Mar			
	(1) leverage volume	(2) real money	(3) total volume
b_1	0.0173**	0.0134*	0.0076*
	0.0084	*0.0075*	*0.0039*
$adj - R^2$	0.0314	0.0212	0.0265
Control	Yes	Yes	Yes
Nobs	586	586	586
Panel C: After QE2020Apr-2021			
	(1) leverage volume	(2) real money	(3) total volume
b_1	-0.0039	-0.0021	-0.0016
	0.0036	*0.0035*	*0.0018*
$adj - R^2$	0.0156	0.0124	0.0154
Control	Yes	Yes	Yes
Nobs	458	458	458

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 5.6 shows the results by using the equation below.

$$P_t = a + b_0 nv_t + b_1(nv_t \times MarketLeverage_t) + \epsilon \tag{5.46}$$

Here we use the whole COVID-19 period, before and after QE, and before the financial crisis.

Table 5.7: Covariance - Market Leverage

	leverage volume	real money	total volume
Whole Period	0.0214	0.0039	-0.0144
Before QE	0.0426	-0.006	-0.0145
After QE	-0.2219	-0.1986	-0.2033

Table 5.7 shows the covariance between $MarketLeverage * NormalizedVolume$ and b_1 in Table 5.5. Here we still perform a rolling regression with a 20-day window.

Table 5.8: High and Low CDS - for Slope Table

2018-2021

	(1) leverage volume	(2)	(3) real money	(4)	(5) total volume	(6)
	High	Low	High	Low	High	Low
b_1	0.0034***	0.0006	0.0035***	0.0010	0.0017***	0.0004
	0.0012	0.0018	0.0012	0.0016	0.0006	0.0008
$adj - R^2$	0.0668	0.0105	0.0582	0.0085	0.0651	0.01
Control	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	522	522	522	522	522	522

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

In Table 5.8, We use equation below to do the regression.

$$P_t = a + b_0 nv_t + b_1(nv_t \times CDS_t) + \epsilon \tag{5.47}$$

where P_t is the exchange rate return, $a$is the intercept, ϵ is the error term and $nv_t$is the normalized volume at time t. We separated our whole period sample into two groups according to the median of CDS .

Table 5.9: High and Low Market Leverage - for Slope Table

2018-2021

	(1)	(2)	(3)	(4)	(5)	(6)
	leverage volume		real money		total volume	
	High	Low	High	Low	High	Low
b_1	0.0027**	-0.0001	0.0026**	0.0002	0.0013**	0.0000
	0.0012	0.0005	0.0012	0.0005	0.0006	0.0003
$adj-R^2$	0.0511	0.0042	0.0449	0.0026	0.05	0.0036
Control	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	522	522	522	522	522	522

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

In Table 5.9, we use the equation below to do the regression.

$$P_t = a + b_0 nv_t + b_1(nv_t \times MarketLeverage_t) + \epsilon \tag{5.48}$$

We separated our whole period sample into two groups according to the median of Market Leverage.

Table 5.10: Volume and Interaction - 2008

	(1)
$Return_{t-1}$	-0.1291*** *0.0361*
$Volume_{t-1}$	-0.0023 *0.0016*
$CDS_{t-1} * Volume_{t-1}$	0.0026* *0.0012*
Controls	Yes
$adj - R^2$	0.3881
Nobs	2,464

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 5.10 shows the coefficient results of equation below by using the sample from Dec.2007 to Mar.2012.

$$r_{it} = \beta_1 r_{i,t-1} + \beta_2 nv_{i,t-1} + \beta_3 \left(nv_{i,t-1} \times CDS_{i,t-1}\right) + \boldsymbol{\delta}' Control_{it} + \gamma_c + \varepsilon_{it} \tag{5.49}$$

Here, we use the double fixed effect and double cluster standard error.

Table 5.11: Volume and Interaction - 2020

	(1) Leveage Volume	(2) Real Money
$Return_{t-1}$	0.0271*	0.0291*
	0.0134	*0.0139*
$Volume_{t-1}$	0.0004*	0.0006***
	0.0002	*0.0001*
$CDS_{t-1} * Volume_{t-1}$	0.0007***	0.0005***
	0.0001	*0.0001*
Controls	Yes	Yes
$adj - R^2$	0.0064	0.0050
Nobs	9,387	9,387

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 5.11 shows the coefficient results of equation below by using the sample from 2018 to 2021.

$$r_{it} = \beta_1 r_{i,t-1} + \beta_2 nv_{i,t-1} + \beta_3 \left(nv_{i,t-1} \times CDS_{i,t-1}\right) + \boldsymbol{\delta}' Control_{it} + \gamma_c + \varepsilon_{it} \tag{5.50}$$

Here, we use the currency fixed effect and the currency cluster standard error. In columns (1) and (2), we separately show the results for leverage volume and real money volume.

Table 5.12: Order Flow and Dealer Leverage - Covid

2018-2021

	(1) Aggregrated	(2) Financial	(3) Non-Financial
$DealerLeverage_{t-1}$	7.7329**	7.9322**	-0.1992
	3.1624	3.0950	2.0620
$DealerLeverage_{t-2}$	-8.2468**	-8.4427***	*0.1959*
	3.3092	*2.9311*	*1.8509*
$adj - R^2$	0.065	0.0689	0.0004
Nobs	46	46	46

*** indicates statistical significance at 10 % level

** indicates statistical significance at 5 % level

* indicates statistical significance at 1 % level

Table 5.12 shows the results of the relationship between order flow and dealer leverage. For the dealer leverage, we use the approach as in He et al. (2017). We generate the market leverage equals to

$$DealerLeverage_t = (MarketEquity_t + BookDebt_t)/MarketEquity_t \tag{5.51}$$

We us the second dealer's monthly data from January 2018 to December 2021 for the regression, and employ robust standard errors. Column (1) shows the results of aggregated order flow, and columns (2) and (3) show the order flow of financial and non-financial clients.

Appendices for Chapter 5

5A Supply Evidence

5A.1 Event-Time Evidence Around Dealer Constraint Shocks

In this section, we use Stacked event-time regressions.

We define CDS change:

$$\Delta CDS_{i,t} = CDS_{i,t} - CDS_{i,t-1}. \tag{5.52}$$

And the stress event indicator:

$$Shock_{i,t} = \mathbf{1}\big(\Delta CDS_{i,t} \geq Q90\big(\Delta CDS_i\big)\big), \tag{5.53}$$

Furthermore, we use the following regression:

$$r_{i,e,\tau} = \alpha_i + \delta_e + \sum_{\tau} \beta_\tau D_{i,e,\tau}\, nv_{i,t_e-1} + \sum_{\tau} \theta_\tau D_{i,e,\tau}\, (nv_{i,t_e-1} \times CDS_{i,t_e-1}) + \rho\, r_{i,t_e-1} + \varepsilon_{i,e,\tau}, \tag{5.54}$$

where

- $r_{i,e,\tau} = r_{i,t_e+\tau}$ is the log return of currency i at event-relative time τ;
- nv_{i,t_e-1} is *lagged normalized volume* (one day before the event) for currency i;
- CDS_{i,t_e-1} is *lagged CDS* (one day before the event);
- $D_{i,e,\tau}$ is an indicator for event time τ ;
- α_i are currency fixed effects ;
- δ_e are event fixed effects ;
- $r_{i,t_e-1} =$ *logreturn_event* is the one day before event-day return used as a control;
- β_τ is the event-time-specific effect of lagged volume;
- θ_τ is the event-time-specific effect of lagged Volume×CDS;
- $\varepsilon_{i,e,\tau}$ is the error term.

Figure 5.10: 2020 - Leverage Volume

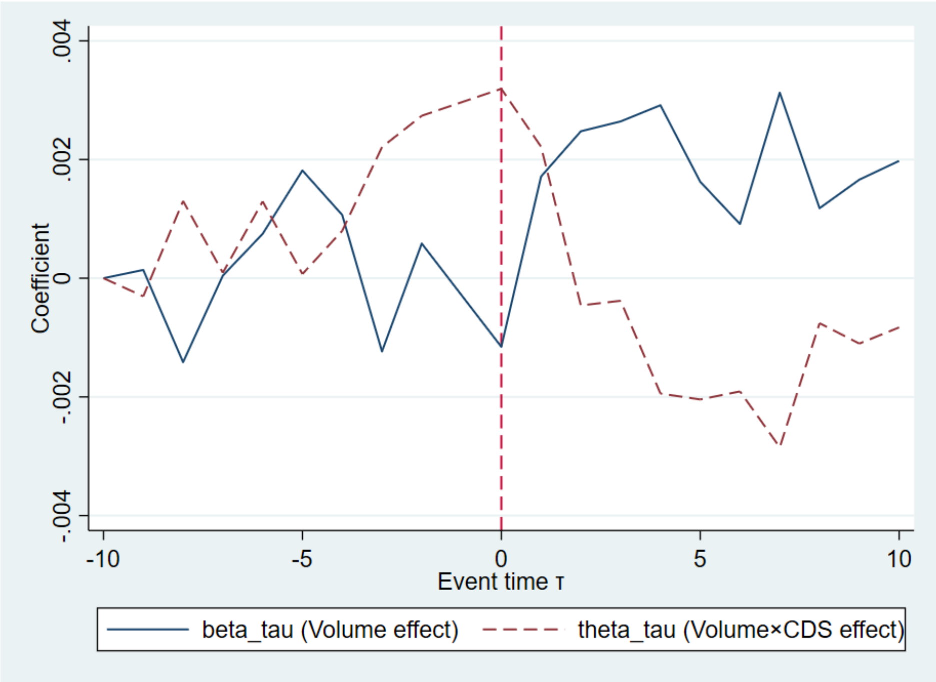
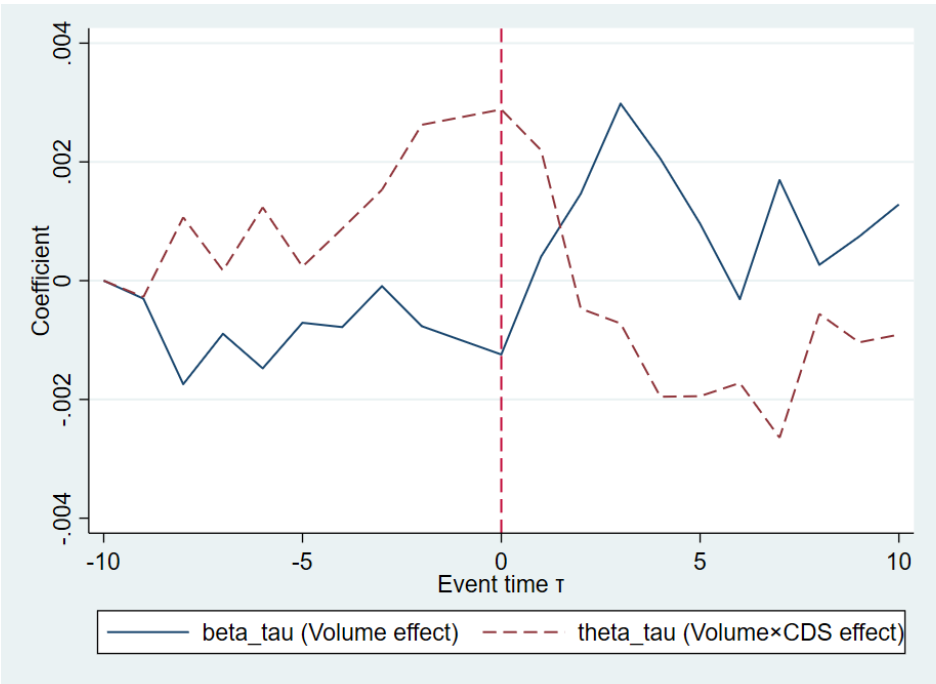


Figure 5.11: 2020 - Real Money



In Figure 5.10 and 5.11, we use equation (5.54) and stacked event-time regression to compute the coefficient of volume and the interaction term.

5B Joint Constraint × Demand Event Study

5B.1 Additional Joint-State Event Studies

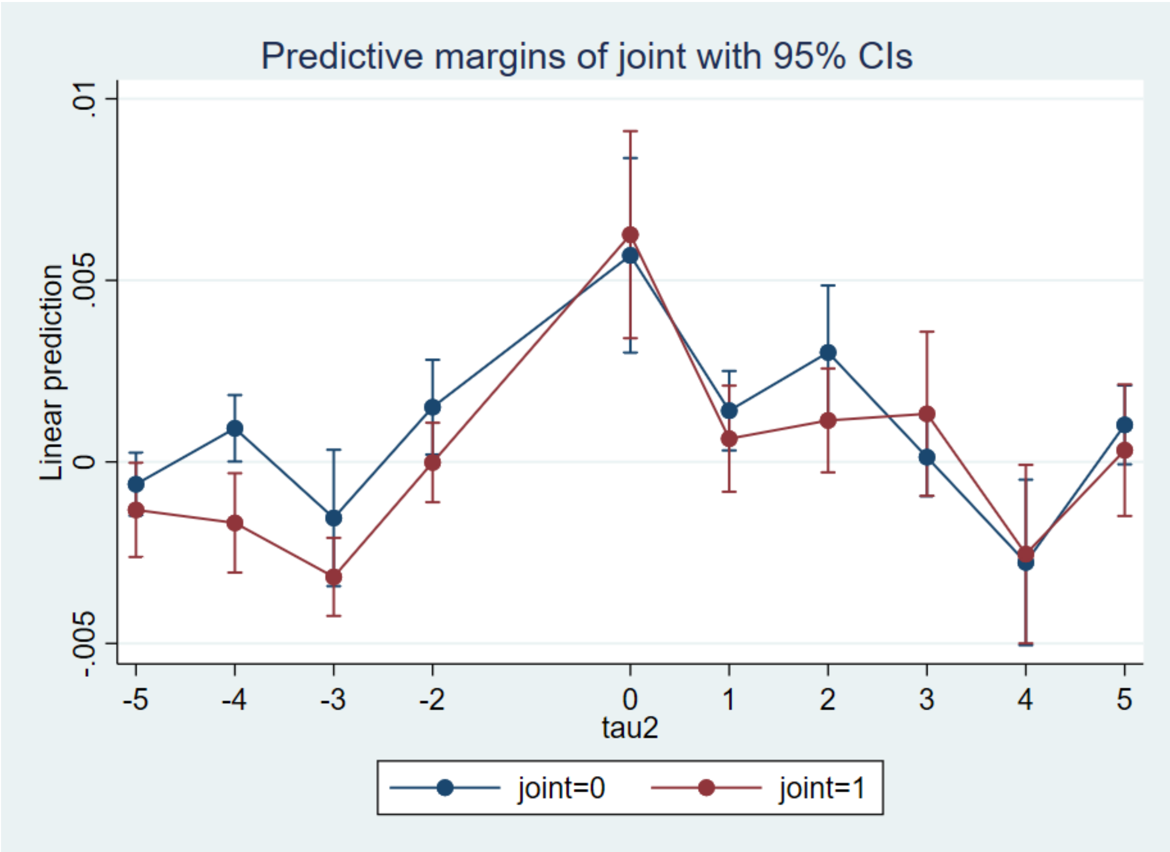


Figure 5.12: 2008-Top 10% change of CDS

Figure 5.12 shows the results of the equation below by using the sample from 2007 Dec. to 2012 Mar.

$$r_{i,e,\tau} = \sum_{\tau \neq -1} \beta_\tau^{Joint} D_\tau \times Joint_{i,e} + \sum_{\tau \neq -1} \beta_\tau^{Other} D_\tau \times (1 - Joint_{i,e}) + \alpha_i + \delta_e + \varepsilon_{i,e,\tau}. \tag{5.55}$$

Here, the red line shows the β_τ^{Joint}, which is the coefficient when both constraints and trading pressure are high. The blue line shows the β_τ^{Other}, which represents the other situations.

5B.2 Placebo Tests

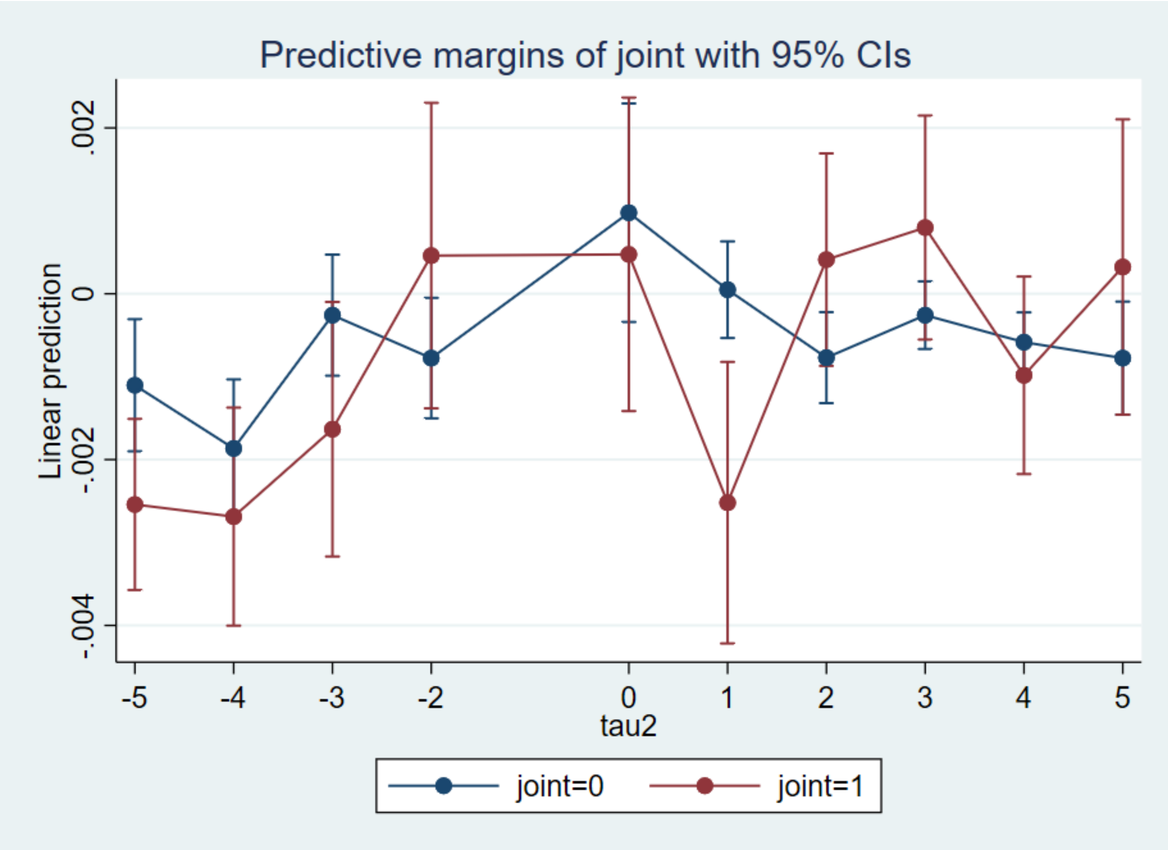


Figure 5.13: Before 2008-Top 10% change of CDS

Figure 5.13 shows the results of the equation below by using the sample from 2003 Nov.. to 2007 Nov.

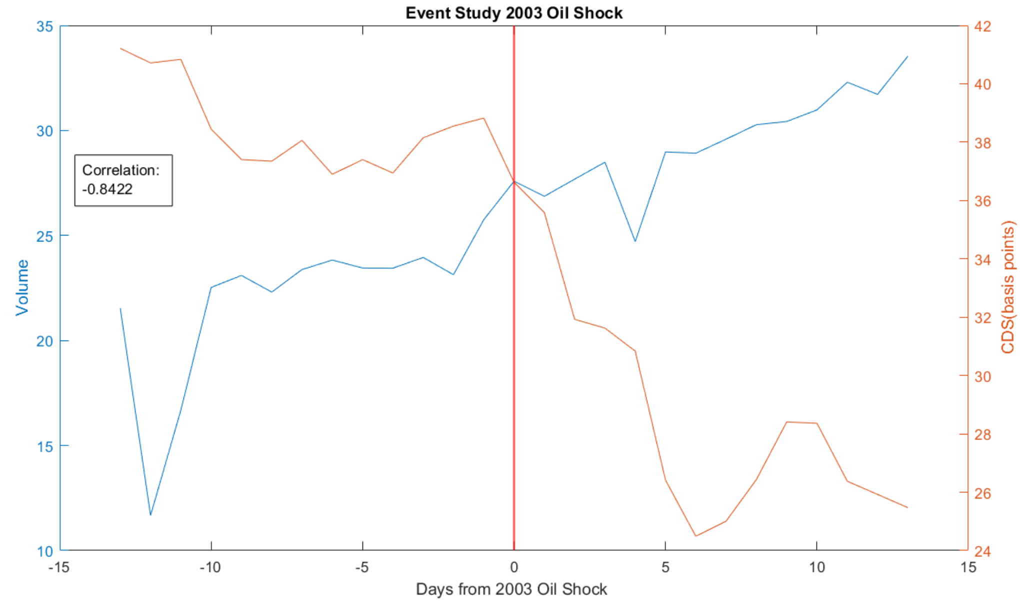
$$r_{i,e,\tau} = \sum_{\tau \neq -1} \beta_\tau^{Joint} D_\tau \times Joint_{i,e} + \sum_{\tau \neq -1} \beta_\tau^{Other} D_\tau \times (1 - Joint_{i,e}) + \alpha_i + \delta_e + \varepsilon_{i,e,\tau}. \tag{5.56}$$

Here red line shows the β_τ^{Joint}, which is the coefficient when both constraints and trading pressure are high. Blue line shows the β_τ^{Other}, which represents the other situations.

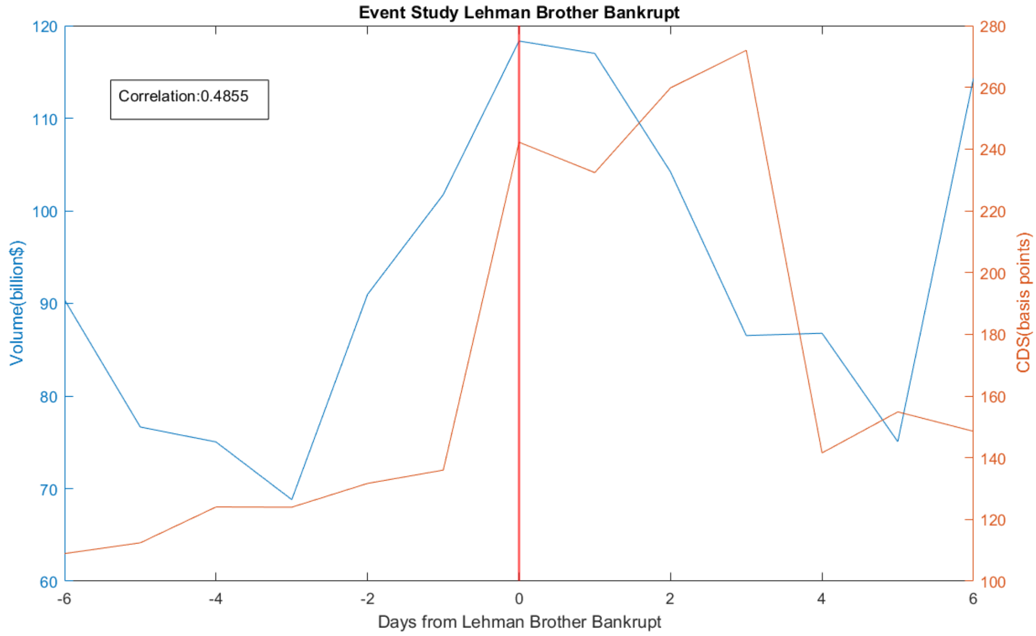
5C Case Study

Figure 5.14: Case Study

(a) Oil Shock - Weekly



(b) Lehman Brother Bankrupt - Weekly



(c) Covid 19 - Daily

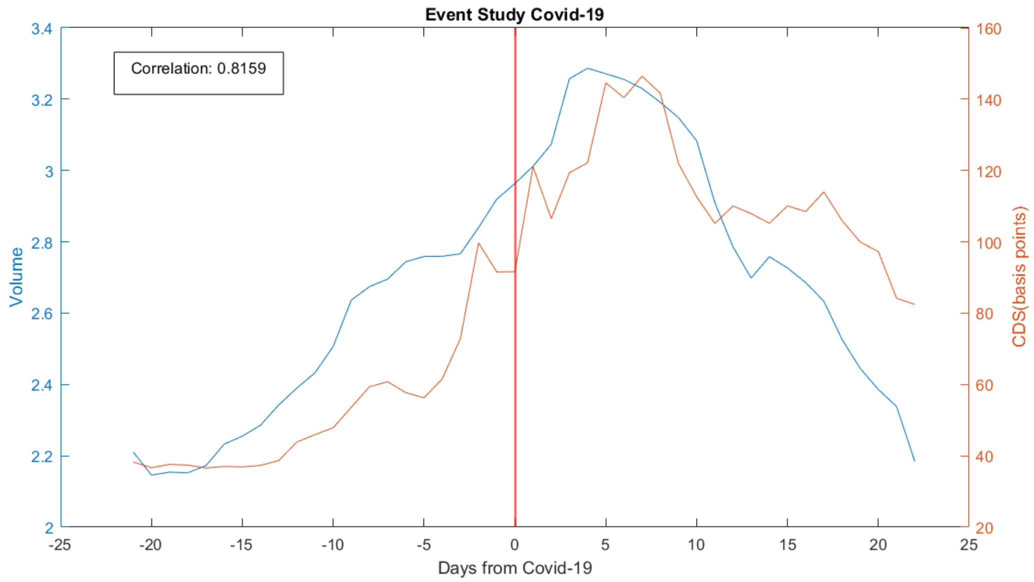


Figure 5.14 shows the FX volume and CDS relationship during the 2003 Oil Shock, the Lehman Brothers bankruptcy and the COVID-19 pandemic. We chose the oil shock and bankruptcy week, also the day on which COVID-19 was defined by the WHO as time 0. Further, we draw the weeks and days before and after time 0.

Chapter 6

Conclusion

This thesis has examined how trading activity, financial intermediation, and dealer balance-sheet frictions shape price formation in foreign exchange markets. Using proprietary bilateral over-the-counter data from two of the largest global dealer banks, the three empirical chapters develop a single argument. The effect of trading on prices cannot be understood in isolation from the capacity and incentives of the intermediaries who absorb that trading. Each chapter isolates one link in this chain, and together they connect the microstructure of currency trading to the intermediary asset pricing framework.

Chapter 2 established that the volume-volatility relationship in FX markets is positive but state-dependent. Across most major currency pairs, trading volume co-moves with both realised and implied volatility, yet the marginal impact of volume declines as activity rises. This pattern indicates that high-volume periods are increasingly composed of non-informational trading such as liquidity provision and inventory rebalancing. Moving from aggregate volume to signed order flow, and then to order flow disaggregated by client type, sharpened the picture further. Buying pressure raises more volatility than selling pressure. Furthermore, retail order flow generates a volatility impact five to seven times larger than institutional flow despite its small share of total turnover. Trade direction and trader identity, not aggregate volume, are the primary drivers of currency volatility. These results caution against treating volume as a simple proxy for information arrival and suggest that volatility models can be improved by incorporating order-flow direction and shifts in the composition of market participants.

Chapter 3 showed that FX trading volume predicts subsequent US dollar appreciation, but only after 2008 and only when dealer balance sheets are constrained. Before the crisis, the same volume carried no predictive content. This structural break is robust across three proxies for balance-sheet stress, namely dealer CDS spreads, intermediary leverage, and the LIBOR-OIS spread, and it holds for both dealers and across the 2008 and 2020 crisis episodes. The predictive information in FX volume is therefore not a permanent feature of the market but a regime-dependent outcome shaped by the post-crisis rise in the cost of dealer balance-sheet capacity. This finding qualifies the prevailing interpretation that volume predictability reflects asymmetric information alone and points to supply-side frictions as a first-order determinant.

Chapter 4 identified the mechanism behind this regime dependence. Balance sheet constraints on market makers reduce the elasticity of US dollar liquidity supply. Consequently, as the costs associated with debt overhang rise, the US dollar supply curve steepens, causing an equivalent level of trading pressure to trigger more pronounced exchange rate volatility. This mechanism operates through the incentives of equity holders rather than through quantity rationing. Constrained dealers continue to intermediate, but only at less favourable prices. On the demand side, surges in dollar demand during crises originate mainly from leveraged financial clients whose trading responds to dealer capital conditions, while the flows of non-financial clients do not. The interaction between capital-dependent demand and a steepening supply curve accounts for the positive relationship between lagged volume and subsequent dollar appreciation during stress.

Taken together, the three chapters make a unified contribution. The state-dependence of the volume-volatility relationship documented in Chapter 2, the conditional predictability of volume established in Chapter 3, and the supply and demand mechanism identified in Chapter 4 all trace back to a common source, which is the constrained and incentive-sensitive capacity of dealers to warehouse risk. The thesis thereby links two literatures that have largely developed in parallel, the microstructure of FX trading and intermediary asset pricing, and shows that the informativeness of trading activity is inseparable from the financial condition of the intermediaries who price it.

These findings carry implications for practice and policy. For exchange rate modelling, they imply that the mapping from order flow to prices should be treated as state-dependent rather than fixed. For risk management, they suggest that periods of impaired dealer capital are precisely when volume shocks translate into disproportionately large price movements, so that measures of balance-sheet stress are informative inputs for forecasting volatility and tail risk. For financial stability policy, they indicate that FX markets become more fragile when dealer balance sheets are impaired by debt overhang, which is directly relevant for assessing the effectiveness of central bank interventions when dollar liquidity is scarce. The analysis also implies that higher equity capital, although costly to shareholders in the short run, can ease intermediation constraints and support market functioning over time.

Several limitations point to directions for future work. The volatility analysis focuses on major currency pairs, and whether the same patterns hold for emerging market currencies remains open. Higher-frequency data would help to separate liquidity-driven from information-driven trading more precisely and to clarify the microstructural channels through which retail participation affects volatility. Finally, extending the balance-sheet analysis to a broader cross-section of dealers would test the generality of the debt overhang mechanism beyond the two institutions studied here. The answer to these questions would further clarify how the health of financial intermediaries governs the formation of exchange rates.

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