BI Norwegian Business School is a leading Nordic research and teaching institution with campuses in the four largest Norwegian cities. Our activity is organized under eight departments covering the range of business research disciplines, and eight BI Research Centres concentrated around themes where we are especially strong.

Departments

- Accounting and Operations Management
- Communication and Culture
- Data Science and Analytics
- Economics
- Finance
- Law and Governance
- Leadership and Organizational Behaviour
- Marketing
- Strategy and Entrepreneurship

BI Research Centres

- Centre for Applied Macroeconomics and Commodity Prices
- Centre for Asset Pricing Research
- Centre for Construction Industry
- Centre for Corporate Governance Research
- Centre for Creative Industries
- Centre for Experimental Studies and Research
- Centre for Health Care Management
- Centre for Household Finance and Macroeconomic Research
- Nordic Centre for Internet and Society
- Simula@BI

For an archive of all our PhD-dissertations/reports, please visit www.biopen.bi.no

BI Norwegian Business School
N-0442 Oslo
Phone: +47 46 41 00 00
www.bi.no

BI Norwegian Business School

Obaidur Rehman • Essays in Empirical Market Microstructure

Series of Dissertations • No. 4–2024

Essays in Empirical Market Microstructure

Obaidur Rehman

No. 4 – 2024
SERIES OF DISSERTATIONS

BI Norwegian Business School

Essays in Empirical Market Microstructure

by
Obaidur Rehman

A dissertation submitted to BI Norwegian Business School
for the degree of PhD

PhD specialisation: Finance

Series of Dissertations 4/2024
BI Norwegian Business School

Obaidur Rehman
Essays in Empirical Market Microstructure:

Series of Dissertations 4/2024

ISBN: 978-82-8247-388-0
ISSN: 1502-2099 (Trykt)
ISSN: 2387-3043 (Elektronisk)

BI Norwegian Business School
N-0442 Oslo
Phone +47 4641 0000
www.bi.no

SVANEMERKET
Trykkeri
2041 0731

TRYKT I
NORGE
NO-598

Skipnes Kommunikasjon AS

Acknowledgements

This dissertation marks the end of a long and enduring academic journey. I am privileged to have had the opportunity to engage with the amazing community of researchers, both at BI and in the wider academic world. These interactions have played an important role in my growth as a scholar. There are some individuals who deserve special recognition.

First and foremost, I owe a huge intellectual debt to my supervisor, Dagfinn Rime, for teaching me the craft of academic research and his continued mentorship throughout my doctoral studies. Dagfinn's valuable advice has been instrumental in the completion of my dissertation.

I also want to express my sincere gratitude to all my coauthors. It has been a pleasure and privilige to collaborate with all of them. Thomas Kjær Paulson who I first met during his job market talk at BI. Thomas's constructive suggestions have not only benefitted our joint work but have also had a transformative impact on shaping my research trajectory. Jens Dick-Nielson for guiding us through our dealer network paper. Olav Syrstad for enlightening me on the intricate institutional mechanics of central bank liquidity provision. Kjell G. Nyborg for inspiring my research interest in collateral frameworks. I have learned immensely from all our exchanges.

I am also thankful to faculty members at the BI Department of Finance, including Sven Klinger, Jiri Woschitz, and Charlotte Østergaard, for their constructive feedback on my research. Q. Farooq Akram at Norges Bank for his support in provisioning the data for the collateral paper. My fellow Ph.D. students, Jonas Barth, and Renata Almeida, for their companionship in this pursuit of knowledge.

I am extremely grateful to my father, Nazar, for his continued encouragement and my wife, Bushra, for being my sounding board and tolerating my endless quibbles about research. Your unwavering support has made this journey possible, and I am truly blessed to have you in my life.

Contents

Introduction

This dissertation consists of three self-contained essays: “Sponsor Support and the Run on Money Market Funds,”, “Dealer Networks and Cost of Immediacy”, and “Collateral Quality and Bidding Behavior in Central Bank Liquidity Auctions.” Below I provide a summary of each of them.

In the first paper, “Sponsor Support and the Run on Money Market Funds,” I examine the implications of a unique feature of the US money market fund (MMF) regulation—the provision for fund sponsors to extend support to their affiliate prime MMFs. These funds play an important role in providing short-term funding to corporations; therefore, their stability is vital for the smooth functioning of the wholesale funding market. I exploit the COVID-19 crisis to examine how differences in the support capacity of fund sponsors relate to the ex-ante risk-taking incentives and crisis outcomes of their affiliate MMFs. My results suggest that MMFs sponsored by financially strong intermediaries exhibit a higher risk profile and suffer higher redemptions during the crisis. The finding provides credence to the view that sponsor support can create a moral hazard by distorting the market discipline of fund managers.

In the second paper, “Dealer Networks and Cost of Immediacy,” we study the role of dealer network position for the cost of immediacy in the corporate bond market. The dealer network in many over-the-counter (OTC) markets exhibits a core-periphery structure. We document a centrality discount for customer-dealer trades and a centrality premium for interdealer trades consistent with recent OTC network models of inventory risk. Our main contribution is to identify the inventory management channel and avoid confounding effects from adverse selection and heterogenous customer clienteles by using trades around bond exclusions. Our results using trades from the entire corporate bond market remain qualitatively similar, which suggests that the inventory management channel is potentially the dominant channel for the average transaction in the corporate bond market.

In the third paper, “Collateral Quality and Bidding Behavior in Central Bank Liquidity Auctions”, we characterize the collateral pledging and bidding behavior of banks in the Norges Bank liquidity auctions. Banks acquire central bank liquidity against eligible collateral. Using a novel dataset that links banks’ pledged and eligible collateral securities at the individual bank level, we find that banks tend to pledge lower-quality collateral from their eligible pool with the central bank. We also find that banks with worse pledged collateral quality draw disproportionally more liquidity in the auctions. The results suggest that banks may engage in strategic pledging behavior if the central bank collateral terms do not adequately reflect market conditions. The findings highlight the importance of the central bank collateral framework for liquidity provision.

Chapter 1

Sponsor Support and the Run on Money Market Funds

Obaidur Rehman, BI Norwegian Business School

Abstract

Prime money market funds (MMFs) frequently receive support from their sponsors during periods of acute market stress. While sponsor support can help restore investor confidence in the fund, it also poses a moral hazard by distorting the market discipline of fund managers. This study exploits the Covid crisis of March 2020 to examine the implications of sponsor support for prime funds' ex-ante risk-taking behavior and crisis outcomes. Consistent with the moral hazard hypothesis, I find that US-based prime MMFs affiliated with strong sponsors engage in higher ex-ante risk-taking behavior. During the crisis, investors do not deem the safety net of strong sponsors as credible, and run more intensely on their affiliate funds. I also examine the behavior of EU-based prime funds, which are prohibited from seeking sponsor support. My results show no differences between sponsor strength, ex-ante risk-taking behavior, or the crisis outcomes for EU-based prime funds.

1.1 Introduction

Money market funds (MMFs) are open-ended mutual funds that invest in a diversified pool of high-quality short-term debt securities and offer on-demand liquidity to investors. The US MMF regulations grant fund sponsors the provision to extend support to their affiliate MMFs. The ”sponsor” is usually an independent asset management entity, an insurance company, or a bank holding company that is affiliated with or a parent company of the MMF. Sponsors are legally independent from their MMFs. Sponsor support encompasses a wide range of sponsor-led interventions to enhance fund liquidity, preserve fund capital, or both.

However, sponsors are not legally obliged to support their MMFs, and as such, the support decision is entirely at their discretion. Nevertheless, the historically high incidence of sponsor support suggests that it is often expected and granted. Sponsor support was indeed a common occurrence during the great financial crisis and more recently during the market turmoil in March 2020.[1]

Kacperczyk and Schnabl (2013) suggests that sponsors' incentives to provide support are largely reputational and driven by the loss of franchise value and negative business spillovers in the event of fund failure. Essentially, a sponsor's decision to provide support is likely an equilibrium outcome of balancing the cost of support against the loss of future fund fee income and sponsor franchise value.

On the one hand, sponsor support provides MMFs with much-needed liquidity and helps to restore investor confidence during periods of market stress. It can act as a stabilizing mechanism and prevent system-wide runs on MMFs. Moreover, through internalizing fund losses, sponsor support can reduce the need for federal bailouts for MMFs (Fisch, 2018). On the other hand, sponsor support can encourage MMFs to engage in higher risk-taking[2]. By creating a private liquidity backstop, the provision for sponsor support can strengthen the risk-taking incentives of MMFs and, therefore, expose them to higher redemption risk during market stress. Thus, there is a potential moral hazard associated with the sponsor support provision. Moreover, Parlatore (2016) argues that the discretionary nature of sponsor support can generate strategic complementarities in sponsors' support decisions and contribute to fragility in MMFs.

The ambiguity surrounding the financial stability implications of discretionary sponsor support is also reflected in its radically different regulatory treatment across the other side of the Atlantic. The EU MMF regulations outrightly forbid fund sponsors from granting support to their affiliate MMFs. The primary concern of EU regulators is that the expectation of support among investors introduces an additional layer of fragility. The failure to deliver support by a sponsor may be deemed as a sign of an underlying weakness, which could invoke a run on the

[1] According to SEC, almost 20% of MMFs received some form of sponsor support over the period August 2007 - December 2008 (Securities and Exchange Commission, 2014)

[2] Kacperczyk and Schnabl (2013) and Chernenko and Sunderam (2014) document a positive flow-performance relation for MMFs, suggesting that MMFs have strong incentives to engage in risk-taking to attract investor flows.

sponsor itself.

Given the aforementioned trade-offs, the efficacy of discretionary sponsor support for the stability of MMFs remains an empirical question. This study exploits the March 2020 run on MMFs to shed light on this important policy dilemma. MMFs that invest in privately issued short-term debt and target institutional investors (institutional prime funds) suffered extraordinary redemptions in March 2020. The assets under management of the US-based institutional prime MMFs and their EU-based counterparts plunged by 30 percent and 25 percent during the second and third week of March. The outflows were contained only following the announcement of the Fed's emergency facilities to backstop MMFs (Li et al., 2021).

In essence, the discretionary nature of sponsor support creates uncertainty about who ultimately bears the risk during periods of stress. Arguably, MMFs with deep-pocketed sponsors are better positioned to receive support and, hence, have higher incentives to engage in risk-taking. Jacewitz et al. (2021) argue that bank holding companies enjoy relatively quick access to cheap and information-insensitive funding sources, such as insured deposits or lender-of-last-resort liquidity through the Federal Reserve discount window, which enable them to provide greater support to their affiliate MMFs. As a result, investors may assign a higher probability of attaining support to bank-sponsored MMFs relative to their non-bank counterparts during periods of high redemption pressure. This is consistent with the findings of Baba et al. (2009), who note that bank sponsors were over-represented among support providers to affiliate MMFs during the great financial crisis.

Using bank affiliation as a proxy for sponsor support capacity, this study examines its interaction with the ex-ante risk-taking behavior and crisis outcomes of institutional prime MMFs. First, I show that bank-affiliated prime MMFs undertake higher risk than their non-bank counterparts before the onset of the crisis. Specifically, I find that bank-sponsored prime MMFs hold a significantly lower fraction of safe assets *(portfolio risk)* and target a more flighty investor base *(investor risk)* in the period leading up to the Covid crisis. The result is robust to controlling for other fund characteristics that correlate with fund risk-taking behavior. These findings are consistent with the moral hazard notion associated with discretionary sponsor support, where funds sponsored by deep-pocketed intermediaries systematically engage in higher risk-taking.

Second, I show that bank-affiliated prime MMFs suffered significantly higher daily outflows during the Covid crisis relative to their non-bank counterparts. Importantly, the relation between sponsor strength and outflows of affiliated MMFs is not confounded by the influence of other economic channels that could amplify redemption pressure on MMFs during the crisis. The results are robust to using alternate proxies for sponsor financial strength. This suggests that investors do not deem the implicit insurance offered by strong sponsors credible and run more intensely on their affiliate funds. Overall, the results suggest that funds affiliated with strong sponsors are inherently more risky and consequently more exposed to run-risk during crisis.

In a separate analysis, I exploit the fact that sponsor support is prohibited in the EU. Therefore, differences in sponsor strength should not affect the ex-ante risk-taking behavior and crisis outcomes of prime MMFs based in the EU. In this manner, the analysis of EU-based prime MMFs provides a suitable falsification test for my original finding. Consistent with my hypothesis, I find that differences in sponsor strength are indeed unrelated with the ex-ante risk-taking and crisis outcomes of prime MMFs based in the EU.

Although my results highlight the potentially destabilizing role of discretionary sponsor support, it is important to stress that the findings do not imply that simply prohibiting discretionary sponsor support would insulate prime MMFs against investor runs. EU-based prime MMFs were also subject to considerable redemptions during the Covid crisis. Rather, the study emphasizes that discretionary sponsor support can distort market discipline, which amplifies run-risk during crisis.

The remainder of the paper proceeds as follows: Section 1.2 highlights the contribution of the study to the existing literature. Section 1.3 provides the relevant institutional background on MMFs and sponsor support. Section 1.4 describes the data used in the analysis. Section 1.5 presents empirical findings. Section 1.6 examines the robustness of the key results, and section 1.7 concludes.

1.2 Related literature and contribution

This paper contributes to the past empirical literature that studies the interaction between sponsor characteristics and affiliate funds' risk-taking behavior and crisis outcomes. In a closely related study, McCabe (2010) examines the role of sponsors during the run on prime MMFs in the 2007 asset-backed-commercial-paper (ABCP) crisis and the 2008 Lehman crisis. The study provides evidence that bank-sponsored prime MMFs were more likely to hold riskier securities leading up to the ABCP crisis and receive sponsor support during the crisis. He interprets this finding as suggestive evidence that sponsor support may distort incentives for prime MMFs sponsored by deep-pocketed financial intermediaries.

However, McCabe does not uncover any association between the bank-affiliation status of prime MMFs and investor flows during the crisis. This contrasts my findings, which show that bank-sponsored prime MMFs experienced higher outflows during the crisis. A possible explanation could be the fundamentally different investor base of prime MMFs over the two periods. Baghai et al. (2022) show that the 2014 SEC MMF reform resulted in a large-scale exodus of investors from institutional prime MMFs. Alternatively, the higher disclosure requirements imposed on MMFs post the reform period enable investors to monitor the funds' risk profile more vigilantly. As a result, investors may redeem more intensely from funds perceived to be more risky in times of heightened systemic risk, regardless of the strength of their sponsors. Last but not least, sponsor support was indeed more widespread during the earlier crisis, which may have alleviated investors' concerns about its credibility.

In another closely related study, Kacperczyk and Schnabl (2013) shows that prime MMFs sponsored by intermediaries with lower reputational concerns took on more risk and suffered higher outflows during the 2008 Lehman crisis. Importantly, the authors emphasize that the funds' risk-seeking incentives are not driven by their sponsors' financial strength but rather by their reputational concerns. However, it is empirically challenging to disentangle these two channels from each other since sponsors with higher reputational concerns are also likely to have greater financial resources.

I build on these studies and examine the implications of sponsor support provision for prime MMFs during the Covid crisis. There are several compelling reasons that warrant a re-examination. First, unlike the previous crises, there was no significant expansion in the risk-taking opportunities for MMFs preceding the Covid crisis. Hence, the Covid shock provides a suitable setting to explore the role of sponsors for MMF outcomes following a period of relative normalcy.

Second, the 2014 SEC MMF reform has dramatically changed the regulatory landscape of prime MMFs, and it is, therefore, important to reassess the role of sponsors in the new environment. Among other changes, prime MMFs lost the ability to mark their shares at a fixed net asset value (NAV) and were required to enforce liquidity fees and redemption gates during extraordinary investor withdrawals. The removal of fixed NAV arguably reduces the need for sponsor support, while the imposition of fees and gates likely increases it. Moreover, as Cipriani and La Spada (2021) show, the SEC MMF reform increased the information sensitivity of prime MMFs and thereby reduced their money-likeness. Historically, sponsor support has played an important role in facilitating the money-like perception of MMFs. However, as investors perceive these funds as less money-like post-reform, this likely reduces the need for sponsor support. Furthermore, unlike in the pre-reform era, investors now enjoy greater transparency regarding the timing and magnitude of sponsor support. This increased disclosure could reinforce investor expectations about future support instances or deter sponsors from extending it. Taken together, these changes have likely altered investors' perception of sponsor support.

Third, this study uses data from regulatory filings to characterize the risk profile and run dynamics of MMFs. This data only became available after 2010, and studies that examine MMF runs during the great financial crisis had to rely on voluntary disclosures by MMFs, which may suffer from selection bias and not offer the same level of accuracy.

Fourth, the empirical design of my study allows for a more comprehensive analysis on the implications of sponsor support. By examining MMFs runs across two distinct jurisdictions, each with a different regulatory approach to sponsor support, we obtain a more nuanced understanding of the relationship between sponsor support, the risk-taking behavior of MMFs, and their crisis outcomes.

This study also contributes to the recent literature that examines fragilities in MMFs over the Covid crisis. Li et al. (2021) focus on the destabilizing role of the fees and gate provision prescribed under the 2014 SEC MMF reform for institutional prime MMFs over the Covid crisis. The authors find that investor redemptions accelerated as the funds' weekly liquid assets (WLA) approached the regulatory threshold of 30% in anticipation of fees and gates.[3] Conversely, Avalos and Xia (2021) shows that large institutional investors ran on prime MMFs irrespective of the funds' WLA. They attribute this finding to the higher risk aversion and liquidity needs of large investors under uncertainty. Focusing on a different aspect of the 2014 SEC MMF reform, Casavecchia et al. (2020) shows that the introduction of the floating NAV for institutional prime MMFs has not eliminated strategic complementarities in investors' redemption decisions. The authors argue that investors continue to have strong incentives to redeem early, particularly during periods of low market liquidity. Cipriani and La Spada (2020) focus on the relevance of switching costs for MMF investors and find that institutional prime MMFs belonging to fund families with a larger share of government MMF experienced higher outflows over the crisis period. In contrast to these studies, I exploit the Covid shock to study the implications of a distinct aspect of US MMF regulation, the provision for sponsor support.

1.3 Institutional background

I first provide a brief description of MMFs domiciled in the US and EU and their supervisory framework. This is followed by a discussion on the relevance of sponsor support for MMFs and its current regulatory treatment across the two jurisdictions.

1.3.1 Money market funds

MMFs are considered an important financial intermediary and serve two critical economic functions. On the asset side, MMFs provide short-term funding to corporations, governments, and municipalities. On the liability side, MMFs provide investors with a safe and flexible cash management vehicle that offers higher yields relative to bank deposits. As of the year-end 2019, the total assets under management of MMFs globally stood slightly above USD 7 trillion, mainly in the US (57%) and the Euro area (20%) (Financial Stability Board, 2020)

MMFs can broadly be classified into two main categories based on their universe of eligible assets: government funds, which can only invest in publicly issued short-term debt securities, including treasury/agency debt as well as repurchase agreements collateralized by these securities, and prime funds, which predominantly invest in privately issued short-term debt securities including commercial paper, certificates of deposit, and asset-backed commercial paper.[4]

MMFs in the US are regulated under rule 2a-7 of the Investment Company Act of 1940, which has undergone several amendments since its inception, the most recent in July 2014. In

[3] Dunne and Giuliana (2021) confirm the findings of Li et al. (2021) for EU-based prime MMFs that are subject to similar constraints.

[4] There is one additional category of MMF in the US - tax-exempt municipal funds that invest in short-term debt issued by municipalities and states. According to the Investment Company Institute, municipal funds accounted for a relatively small fraction (4%) of the US MMF assets as of the year-end 2019.

general, rule 2a-7 enforces strict requirements on the credit, maturity, and diversification profile of MMFs, and the exact requirements vary by the type of MMF. Prime MMFs—the subject of this study—are segregated into two types based on their investor profile. Retail funds can only be marketed towards individual investors, which the regulation defines as all "natural persons", and institutional funds mainly cater to institutional accounts, including, but not limited to, corporate treasurers, investment funds, insurance companies, and pension funds. Aside from differences in investor profiles, the most significant difference between the two fund types is that retail funds can quote fixed NAV using the amortized cost method, but institutional funds have to quote variable NAV using the mark-to-market method.

MMFs in the EU are regulated under the 2017 EU Money Market Fund Regulation and are denominated in three main currencies: EUR (40%), USD (36%), and GBP (24%) (European Fund and Asset Management Association, 2020). USD-denominated prime MMFs are offered either as variable NAV or "low-volatility" NAV (LVNAV), where the latter represents the dominant category and is the subject of this study. USD LVNAV funds (hereafter EU prime funds) are allowed to quote a fixed NAV unless their mark-to-market NAV deviates by more than 20 basis points. Moreover, unlike their US counterparts, EU prime funds exclusively cater to institutional investors.

A key innovation of the MMF reform common to both jurisdictions is the provision of fees and gates. Prime MMFs have the option to charge investors liquidity fees or suspend redemptions if the fund's weekly liquidity assets (WLA) fall below the regulatory minimum of 30%.[5] For the EU prime funds, the introduction of fees/gates at the 30% WLA threshold additionally requires that the fund's daily net redemptions exceed 10% of its total assets.[6] Moreover, the fees/gate become binding in both jurisdictions once the fund's WLA drop below 10%. Table A1 in the Appendix provides additional details on the regulatory features of US- and EU-based prime MMFs.

1.3.2 Sponsor support

While MMFs do not have access to explicit federal deposit insurance, investors have perceived them as functionally equivalent to bank deposits for much of their history. To some extent, this perception of safety has been facilitated through sponsors' support actions. The significance of sponsors for MMFs is also reflected in the fact that the sponsor's financial strength constitutes an important input in the overall rating of its MMF (Fitch Ratings, 2021). Sponsor support is not merely theoretical but has been prevalent throughout the history of MMFs. Moody's Investor Services (2010) estimate over 200 instances when MMFs domiciled across the US and EU received support from their sponsors between 1980 and 2009. Furthermore, Brady et al. (2012)

[5] WLA constitute cash, treasuries, certain agency notes that mature within 60 days, and other assets with a one-week maturity.

[6] Hence, the EU prime funds have slightly more strict criteria for the imposition of discretionary fees/gates.

document thirty-one instances between 2007 and 2011 where prime MMFs would have broken the buck in the absence of sponsor support.[7] The great financial crisis shocked confidence in the perceived safety of MMFs when the largest prime fund, Reserve Primary Fund, representing approximately 5% of the industry assets, broke the buck largely due to losses stemming from its exposure to Lehman's commercial paper. Given the gravity of the shock, sponsor support did not prove adequate to contain the fund losses, and the Reserve Primary Forced was eventually forced to liquidate.

In the US, sponsor support is regulated under rule 17a-9 of the Investment Company Act of 1940, which grants fund sponsors the discretion to provide financial support to MMFs. The support includes a wide range of sponsor-led interventions, including capital contributions, purchase of any defaulted or devalued security at par, execution of credit guarantees, capital support agreement, or any other similar action intended to increase or stabilize the value of the fund's portfolio.

Bank sponsors are further subject to section 23A of the Federal Reserve Act, which limits the aggregate amount of "covered transaction" between a bank and its affiliate.[8] However, the Federal Reserve routinely exempts transactions between banks and their affiliate MMFs from the 10% quantitative limit in periods of acute market distress.

Prior to the 2014 SEC MMF reform, investors had limited transparency with respect to the timing and magnitude of sponsor support except under certain instances when MMFs sought assurances from the SEC staff in the form of no-action letters. The MMF reform clarified the scope of what constituted sponsor support and required funds to publicly disclose any instance of sponsor support in the form N-CR within one business day of receiving the support.[9] The disclosure must include the nature, amount, reason, and terms of the support and the relationship between the entity providing the support and the fund. The high disclosure requirements are intended to provide near real-time transparency regarding sponsor support actions, enabling regulators, investors, and other market observers to monitor these important developments more expeditiously. In the SEC's view, this elevated level of transparency would counter the negative externalities arising from the discretionary nature of sponsor support. However, as Fornasari (2018) notes, the greater level of transparency may have the unintended effect of reinforcing investor expectations about future support instances.

The EU enacted its version of MMF reforms in 2017. Unlike their US counterparts, the EU

[7]"Breaking-the-buck" refers to a situation in which the per share marked-to-market value of the fund's NAV falls to 99.5 cents or less, and as a result, the fund loses the ability to quote its NAV at a fixed price of one dollar per share.

[8]"Covered transaction" include the purchase of assets by a bank from an affiliate, the issuance of a guarantee by a bank on behalf of an affiliate, and certain other transactions. Section 23A stipulates that the aggregate amount of a bank's covered transaction with a particular affiliate should not exceed 10% of the bank's capital stock and surplus.

[9]In addition, MMFs are also required to report historical instances of sponsor support over the past ten years in their statement of additional information (SAI).

regulators imposed an outright ban on sponsor support. This is codified under Article 35 of the EU money market fund regulation, which prohibits any direct or indirect third-party actions intended to bolster fund liquidity or stabilize its net asset value (Council of European Union, 2017).

1.4 Data description

1.4.1 Data sources

The data for this study has been gathered from multiple sources. First, the daily fund-level data on flows, yields, liquidity, and maturity characteristics is obtained from Crane Data for the period January - April 2020. This dataset provides coverage for both the US- and EU-domiciled MMFs and was used in recent studies, including Avalos and Xia (2021) and Bouveret et al. (2021). Second, monthly data on the portfolio composition of the US and EU prime funds is obtained from the SEC form N-MFP and Crane international money fund portfolio holdings report, respectively. Third, I retrieved information on the required minimum investment amount for the US prime funds from form N-MFP and the EU prime funds from fund annual prospectuses.[10] Fourth, I use the SEC form N-CSR filings to identify funds that received sponsor support during the Covid crisis. Finally, I collect information on sponsor characteristics from Bloomberg.

An essential aspect of my analysis is the classification of funds with respect to their bank affiliation status. Crane Data provides a flag for funds that are sponsored by banking entities. I validate the relationship between each MMF and its sponsor by manually searching the fund prospectuses. My initial sample includes 44 US institutional prime MMFs that collectively manage approximately USD 625 billion as of the beginning of 2020. However, 11 of these funds are so-called "internal funds," and I exclude them from my analysis. Internal MMFs are used as a cash management vehicle for related entities, such as other funds in the fund complex, and are not available to outside investors.[11] Table A2 in the Appendix contains the list of internal funds and their respective assets under management.[12] The total assets of internal funds are comparable to their public counterparts. I also exclude feeder funds that invest all their funds into master funds. The final sample comprises 32 US and 21 EU institutional prime MMFs.

Table A3 in the Appendix contains the list of sponsors that are part of my sample along with their total fund assets in each jurisdiction. There is a total of 26 unique fund sponsors, with half

[10] Typically, a fund offers multiple share classes with different minimum investment requirements. I use the minimum investment amount pertaining to the largest share class of the fund.

[11] Witmer (2019) shows that internal MMFs face fewer strategic complementarities in their investor redemption decisions and suffer lower outflows during a crisis. Moreover, internal funds are also not part of the *iMoneyNet* MMF dataset widely used in the academic literature. Hence, the decision to exclude them is also important for consistency with related studies.

[12] To identify internal funds, I use information from Crane Data and the information on investor composition from the fund's statement of additional information (SAI)

of them offering prime funds across both the US and EU. The top 3 sponsors in the US account for about 45% of the total assets, and the top 3 sponsors in the EU account for about 60% of the total assets. This indicates the highly concentrated nature of the prime fund industry. Moreover, about half of the sponsors are organized as bank holding companies.

1.4.2 Descriptive statistics

Table 1.1 presents summary statistics for both the US and EU prime funds over the two months before the onset of the crisis. Panels A and B provide summary statistics for the US and EU prime funds, respectively. The average US fund manages approximately USD 8.4 billion, is 20 years old, has a weighted asset maturity of about 30 days, and offers a seven-day gross yield of 1.82%. In terms of liquidity profile, the average fund holdings of daily and weekly liquid assets are above the regulatory thresholds at 32% and 43%, respectively. The average fund charges an expense ratio of 16 basis points, and the average minimum required investment is approximately USD 32 million.

Comparing the two fund types, I find that the bank-affiliated funds in the US cater to larger investors relative to the investor profile of non-bank-affiliated funds. The difference is economically significant, with bank funds requiring about USD 50 million more in minimum investment from their investors.

The portfolio compositions also vary significantly across the bank and non-bank funds. While the average bank fund invests about 13% of its total assets in safe securities (treasury/agency debt and repos collateralized by these securities), the average non-bank fund allocates 23% of its total assets to safe securities. The highly significant 10 percentage point difference in safe asset holdings suggests that non-bank funds are more conservatively managed relative to bank funds.

Although I do not uncover any statistically significant differences in the liquidity and maturity characteristics across the two fund types, the results based on investor and portfolio composition show that the bank-affiliated funds in the US target larger investors and invest less in safe assets prior to the onset of Covid crisis.

[INSERT TABLE 1.1]

Focusing next on the EU-domiciled funds, the average fund manages approximately USD 17 billion, is 19 years old, has a weighted asset maturity of about 37 days, and offers a seven-day gross yield of 1.84%. In terms of liquidity profile, the average fund holdings of daily and weekly liquid assets are above the regulatory thresholds at 28% and 41%, respectively. The average fund charges an expense ratio of 17 basis points, and the average minimum required investment is approximately USD 60 million.

Interestingly, unlike their US counterparts, bank- and non-bank-affiliated funds have markedly similar characteristics in the EU. The two fund types are statistically indistinguishable across all fund characteristics, including portfolio and investor composition. Overall, the evidence based on summary statistics suggests that the sponsor type interacts in important ways with the fund's risk profile in the US, where sponsor support is allowed, but not in the EU, where sponsor support is prohibited.

1.4.3 Money market funds during the Covid crisis

Institutional prime MMFs came under significant strain in March 2020 as the uncertainty around Covid amplified. Figure 1.1 shows that institutional prime funds across both the US and EU were subject to large-scale investor redemptions. The total assets under management of the US- and EU-domiciled prime funds shrunk in excess of USD 90 billion during the month of March. Some fund sponsors in the US extended support to their prime funds in an attempt to prevent their funds' share of weekly liquid assets from falling below the regulatory threshold of 30%.[13]

Given the severity of the crisis, the Fed was forced to intervene through extraordinary measures to backstop MMFs. On 18th March, the Fed announced the establishment of Money Market Liquidity Facility (MMLF) that was subsequently operationalized on the 23rd of March. Under the MMLF, US-based MMFs could offload illiquid securities (including commercial paper and certificate of deposits) with the Fed and thus bolster their liquidity buffers.[14] While the US-based MMFs directly benefited from MMLF, the facility also had positive spillovers for EU-based funds through its stabilizing effect on the underlying money market securities. The establishment of the MMLF effectively eliminated the need for any sponsor support for MMFs as the Fed stood ready to extend liquidity support to troubled MMFs. This is consistent with no observed instance of sponsor support actions following the implementation of the MMLF.

[INSERT FIGURE 1.1]

In terms of fund type, bank-affiliated funds in the US experienced sharper outflows during the crisis relative to non-bank-affiliated funds. By the time the MMLF was implemented, the cumulative outflows stood at 34% for bank-affiliated funds and 27% for non-bank-affiliated funds. Furthermore, as illustrated in the right Panel of Figure 1.1, there are clear differences in distribution densities of cumulative flows across bank and non-bank affiliated funds in the US. This stands in contrast to the experience of EU funds, where I do not observe any marked difference in the cumulative outflows suffered by bank- and non-bank-affiliated funds over the crisis period.

Figure 1.2 illustrates the average daily flows of bank- and non-bank-affiliated funds across the two jurisdictions over the pre-crisis and crisis periods. Unlike the EU funds, bank-affiliated funds in the US had significantly higher average daily outflows relative to their non-bank

[13] This included three bank-sponsored prime funds, and the collective amount of support amounted to USD 3.7 billion.

[14] Li et al. (2021) show that prime MMFs with lower WLAs actively used MMLF to enhance their liquidity profile.

counterparts during the crisis period. Conversely, both fund types exhibited similar flows across both jurisdictions in the pre-crisis period.

[INSERT FIGURE 1.2]

1.5 Empirical strategy and results

1.5.1 Sponsor strength and risk-taking

Table 1.1 provides interesting stylized facts on the differences between the portfolio and investor profile of bank- and non-bank-affiliated prime funds. In this section, I formally examine the relationship between funds' risk-taking behavior and their sponsors' strength. Specifically, I estimate the following cross-sectional regression separately for the US and EU funds over the two months prior to the start of the Covid crisis.

$$Risk_i = \beta_0 + \beta_1 Bank_i + \beta_2 \delta_i + \epsilon_i \tag{1.1}$$

where $Risk_i$ refers to either the *portoflio risk*, proxied by the share of fund assets invested in treasury and agency securities, including repos backed by these securities, or *investor risk*, proxied by the logarithm of required minimum investment for the fund. $Bank_i$ is a dummy that equals one if the sponsor is a banking entity and is used to proxy for the strength of the MMF sponsor. As discussed earlier, banks have cheaper and wider access to funding sources and, therefore, face fewer financial constraints in supporting their affiliate funds.[15] δ_i is a vector of fund-specific controls, including the logarithm of fund size, weighted asset maturity, age, and either of the two risk proxies. The results are reported under Table 1.2. Panels A and B show the results for the US and EU funds, respectively. The first column corresponds to portfolio risk, and the second corresponds to investor risk.

[INSERT TABLE 1.2]

First, I find that bank-sponsored MMFs based in the US have a lower fraction of safe assets in their portfolio. The difference is both statistically and economically significant. The coefficient estimate of -8.78 implies that bank-affiliated funds, on average, invest 8.78% less in safe assets relative to non-bank funds while controlling for other fund characteristics. This suggests that a fund with a stronger sponsor has a lower concentration of safe securities in its portfolio. Safe assets offer lower returns than risky assets; hence, funds have strong incentives to shift allocations away from safe securities to bolster yields and attract investor inflows (Chernenko and Sunderam, 2014). Affiliation with a financially strong sponsor can further reinforce these risk-seeking incentives. This is consistent with the findings of McCabe (2010), which show that

[15] Jacewitz et al. (2021) show that investors value the shadow insurance available to MMFs sponsored by bank holding companies and are willing to pay a premium for it through higher fund fees.

prime MMFs affiliated with stronger sponsors were more likely to hold riskier securities in the period leading up to the 2007 ABCP crisis.

Second, I find that bank-sponsored MMFs in the US also require a higher minimum investment amount from their investors. Importantly, this result is robust to the inclusion of fund size. The coefficient estimate of 2.33 suggests that bank-affiliated funds, on average, require 10.27 times ($e^{2.33}$) higher capital in minimum investment from their investors, conditional on all else being equal. As investment amount is commonly used in the literature to proxy for investor sophistication, the evidence is consistent with more sophisticated investors bunching in bank-affiliated funds. Sophisticated investors possess superior monitoring capabilities and, given their higher skin in the game, have greater incentives to actively monitor developments in financial markets (Gallagher et al., 2020). Consequently, these investors are more likely to anticipate and preempt less sophisticated investors in their redemption decisions. Schmidt et al. (2016) argue that MMFs with a higher concentration of sophisticated investors exhibit stronger strategic complementarities, as each investor is aware that others with similar information are prepared to strategically redeem their investments. Alternatively, as Avalos and Xia (2021) argues, larger investors may have potentially higher liquidity needs under uncertainty and may, therefore, display more flighty behavior.

As noted earlier, sponsor support is explicitly prohibited in the EU. Therefore, we should not expect any differences in the risk-taking behavior of EU prime funds based on the financial strength of their sponsors. In this way, the analysis of EU funds provides a suitable falsification test for the findings above. As shown in Panel B, sponsor strength is not related to either of the two risk proxies for EU-based prime funds. In fact, bank-sponsored funds have a higher share of safe assets, although the difference is not statistically significant.

The results indicate that sponsor strength has implications for the funds' risk appetite. MMFs with stronger sponsors exhibit higher portfolio and investor risk. This lends credence to the notion of moral hazard associated with sponsor support, where funds with stronger sponsors tend to engage in higher risk-taking. Importantly, since a fund's sponsor type is a fixed characteristic, a MMF is unlikely to switch its sponsor based on its risk-taking preferences, thus ruling out any reverse causality concerns. Moreover, when the sponsor support channel is absent, as in the case of EU-based funds, the funds' risk-taking behavior is unrelated to the strength of their sponsors.

1.5.2 Sponsor strength and run-risk

In this section, I examine how differences in sponsors' financial strength relate to the stability of their affiliate funds during a period of acute market stress. On the one hand, funds sponsored by financially strong intermediaries are more likely to receive support, which could enhance investor confidence and mitigate run-risk. On the other hand, as shown in the previous section, funds sponsored by financially strong intermediaries also exhibit higher risk, which could undermine investor confidence and heighten run-risk. Whether investors view the implicit insurance offered by strong sponsors as credible is an empirical question.

I exploit the Covid financial market meltdown as a quasi-natural experiment to examine the relation between sponsor financial strength and affiliate fund flows. The crisis was primarily driven by concerns over the transmission of the Coronavirus. Therefore, it qualifies as a valid exogenous shock for analyzing how variation in the financial strength of sponsors relates to the flows of their affiliate prime funds. The "crisis" period begins on March 6, when institutional prime funds began to experience large-scale redemptions, and ends on March 20, the last business day before the implementation of MMLF. With the establishment of MMLF, the Fed effectively eliminated the need for sponsor support, as it stood ready to extend support to prime funds. The "normal" period begins at the beginning of February and ends on March 5.[16] I estimate the following difference-in-difference regression specification at the fund level:

$$Flow_{i,t} = \beta_0 + \beta_1 Bank_i + \beta_2 Crisis_t + \beta_3 Crisis_t \times Bank_i + \delta X_{i,t} + \epsilon_{i,t} \tag{1.2}$$

where $Flow_{i,t}$ is the daily percentage change in the AUM of fund i on day t, winsorized at the 0.5% and 99.5% levels. $Bank_i$ is a dummy that equals one if the sponsor of fund i is a banking entity. $Crisis_t$ is a dummy that equals one if day t is in the crisis period. $\delta_{i,t}$ is a vector of lagged fund-specific controls commonly used in the literature to explain fund flows. These include the fund's share of weekly liquid assets, the share of safe and risky assets, gross seven-day yield, age, and the natural logarithm of fund size and minimum investment amount. Most of the variables are available at a daily frequency, except for the portfolio share of safe and risky assets, which are only available at a monthly frequency. Standard errors are two-way clustered at the fund and day levels to control for auto-correlation and cross-correlation.

[INSERT TABLE 1.3]

I estimate equation (1.2) separately for the US and EU prime funds. Table 1.3 reports the results for US prime funds. The main coefficient of interest is β_3, which captures the differential effect of the crisis on the daily flows of bank-affiliated funds relative to non-bank-affiliated funds. As shown in column 1, β_3 is negative and highly statistically significant, which suggests that prime funds sponsored by banks experienced larger outflows during the Covid crisis compared to those sponsored by non-bank intermediaries. Specifically, I find that bank-sponsored funds suffered 2.21% higher daily outflows relative to non-bank funds during the crisis period. Given that the average change in the daily assets of non-bank funds during the crisis is -1.26% ($\beta_0 + \beta_1$), the coefficient estimate of -2.21 on the interaction term implies that bank-sponsored funds had 2.5 times higher (-3.09%/-1.26%) daily outflows during the same period. This is an economically significant difference. To control for time-varying aggregate shocks that may affect fund flows, I include day fixed effects in column 2. This is particularly important given the significant developments in financial markets and news about the coronavirus during the sample period.

[16] This is in line with the crisis window used in Cipriani and La Spada (2020).

However, my results remain virtually unchanged. Next, in column 3, I additionally control for any time-invariant unobservable fund characteristics, but the results are again unaffected. Finally, I introduce fund-level controls in columns 4 and 5, which result in a slight reduction in the magnitude of β_3; nevertheless, it remains highly statistically significant. Overall, my main result is robust to a battery of different specifications.

These results clearly show that bank-sponsored prime funds based in the US had worsened financial outcomes during the Covid crisis. This may seem counter-intuitive since these funds are more likely to receive financial support from their sponsors, which should help restore investor confidence. However, as shown in Panel A of Table 1.2, bank-sponsored prime funds in the US also had a higher risk profile before the crisis, which would be consistent with their higher observed outflows. Investors do not perceive the safety net provided by strong sponsors as credible and run more intensely.

The results for the EU funds are reported under Table 1.4. The coefficient on the interaction term, although slightly negative, is not statistically significant under any specification. This suggests that bank and non-bank funds experienced similar flows during the crisis. This result conforms with the findings reported under Panel B of Table 1.2, where I do not uncover any significant relation between sponsor strength and the risk profile of bank and non-bank funds based in the EU.

[INSERT TABLE 1.4]

1.5.3 Pre-trends

An underlying assumption of my difference-in-difference specification is that the flows of the bank- and non-bank-affiliated funds exhibited similar trends over the period preceding the Covid crisis. I formally check for this assumption by augmenting equation (1.2) with lagged interaction terms to check the sensitivity of fund flows to the sponsor type for US-based funds during the pre-crisis period.

$$Flow_{i,t} = \beta_0 + \beta_1 Bank_i + \sum_{t \neq -1} \beta_2 Crisis_t + \sum_{t \neq -1} \beta_3 Crisis_t \times Bank_i + \delta X_{i,t} + \epsilon_{i,t} \tag{1.3}$$

where t spans the period 5 weeks before the onset of the crisis until its end. The week immediately preceding the crisis defines the baseline period. The results reported under Table 1.5 show that none of the pre-crisis interaction terms are statistically significant. This suggests that both bank and non-bank funds experienced similar changes in their flows in the period leading up to the crisis, and the deviation only occurred during the crisis.

[INSERT TABLE 1.5]

1.5.4 Sponsor strength, risk-taking, and run-risk

The regression results reported in Panel A of Table 1.2 and 1.3 indicate that funds sponsored by financially strong intermediaries exhibit a higher ex-ante risk profile and higher run-risk during the crisis. However, these findings, taken in isolation, may not be sufficient to establish a direct link between the sponsor's strength, the ex-ante risk-taking behavior, and the crisis outcomes of funds. To address this, I estimate a two-stage regression for the US-based funds. The goal of this exercise is to examine whether funds affiliated with strong sponsors are inherently riskier and, consequently, more prone to run-risk during the crisis. In the first stage, I estimate a logistic regression on the cross-section of funds over the pre-crisis period. I regress the funds' bank-affiliation indicator on its risk proxies. Subsequently, I estimate a panel regression in the second stage by regressing fund-level daily flows during the crisis on the fitted probabilities obtained from the first stage. This is formalized below.

$$Pr(Bank_i = 1) = \phi\big(\beta_0 + \beta_1 Safe_i + \beta_2 \log(InvestmentAmount_i) + \epsilon_i\big) \tag{1.4}$$

$$Flow_{i,t} = \beta_0 + \beta_1 \widehat{Pr(Bank_i)} + \beta_2 \delta_{i,t} + \theta_t + \epsilon_{i,t} \tag{1.5}$$

where $\phi(\cdot)$ is the logistic function. $Safe_i$ is the average share of fund assets invested in safe securities. $Investment\ Amount_i$ is the required minimum investment amount of fund. $\widehat{Pr(Bank_i)}$ are the fitted probabilities obtained from the first-stage regression. $\delta_{i,t}$ is a vector of lagged fund-specific controls, including weekly liquid assets, flow, weighted asset maturity, age, and the logarithm of fund size. θ_t denotes day fixed effects.

The first- and second-stage regression results are reported under panels A and B of Table 1.6, respectively. In the first-stage results, I observe that funds with a lower fraction of safe assets and a higher minimum investment amount are more likely to be affiliated with a banking entity. The $p-value$ from the Wald test of joint significance of coefficients is below the significance level of 5%, indicating that both the risk proxies jointly contribute to predicting the bank-affiliation status of a fund. Next, in the second-stage results, I find that funds with a higher probability of being sponsored by a banking entity experience higher outflows during the crisis period.

[INSERT TABLE 1.6]

The results provide additional suggestive evidence that riskier funds are more likely to be sponsored by financially strong intermediaries and experience higher investor redemptions during the crisis period.

1.6 Robustness

1.6.1 Alternative channel

Li et al. (2021) highlight the destabilizing role of liquidity restrictions imposed on prime funds by the 2014 MMF reform during the Covid crisis. Specifically, they show that prime funds with weekly liquid assets closer to the regulatory threshold of 30% suffered higher outflows during the crisis, as investors ran preemptively in anticipation of WLA-contingent redemption gates and liquidity fees. Although I do not uncover any significant differences between the WLA profile of bank- and non-bank-sponsored funds prior to the crisis (Panel A Table 1.1), it is possible that bank-sponsored funds had systemically lower WLA levels during the crisis, which left them more vulnerable to disorderly redemptions. To address this concern, I introduce the interaction of fund-level two-day lagged *WLA* and *Crisis* dummy as an additional explanatory variable in equation (1.2). Consistent with Li et al. (2021), Table 1.7 shows that fund outflows were highly sensitive to their WLA levels during the crisis. More importantly, the coefficient of the interaction between *Bank* and *Crisis* remains negative and highly significant. This suggests that the *Bank* variable does not merely proxy for low WLA and has an effect on fund outflows that is orthogonal to the effect of WLA.

[INSERT TABLE 1.7]

1.6.2 Alternative measures of sponsor financial strength

Thus far, I have relied on the banking status of the MMF sponsor to proxy its financial strength. In this section, I employ alternative proxies for measuring the financial constraints of the fund sponsors and examine their relationship with fund flows during the Covid crisis.

First, I sort funds into two categories based on whether their sponsoring entity belongs to the group of globally systematically important banks (GSIBs) as of the end of 2019. The Financial Stability Board classifies financial institutions as GSIBs based on five key indicators: size, interconnectedness, cross-jurisdictional activity, substitutability, and complexity. Given their systemic importance, GSIBs enjoy implicit government guarantees, which reduces their funding costs (Ueda and Di Mauro, 2013). Therefore, one could argue that GSIB sponsors have a higher capacity to support their affiliate funds, which could incentivize higher risk-taking and, as a result, expose their funds to higher run-risk during a crisis. I re-estimate equation (1.2) for US-based funds where the $Bank_i$ dummy is replaced with the $GSIB_i$ dummy. The baseline category now comprises funds sponsored by non-banks and non-systematically important banks. The results reported in column 1 of Table 1.8 show that funds affiliated with GSIBs suffered significantly higher daily outflows during the Covid crisis relative to funds affiliated with non-GSIBs. This supports my earlier finding that prime MMFs sponsored by deep-pocketed entities experience worse outcomes during a period of market stress. Column 2 of Table 1.8 reports the regression results excluding funds sponsored by non-bank intermediaries from the baseline. The coefficient on the interaction term *GSIB* $\times$ *Crisis* is still negative but no longer statistically significant, likely due to the substantial loss in sample size.

[INSERT TABLE 1.8]

Second, I proxy sponsor strength based on their total assets at the end of 2019. Arguably, sponsors with larger asset holdings have greater means to support their affiliate funds. I separately assign bank and non-bank sponsors into two categories based on whether their assets are above the median assets of their respective groups. The omitted category is composed of funds sponsored by non-bank institutions with below-median assets. The results reported in column 3 of Table 1.8 show that funds sponsored by large banks suffer the highest daily outflows during the crisis. The interaction term *Large Bank* $\times$ *Crisis* is highly statistically significant and has higher economic significance relative to the coefficient estimate associated with *Small Bank* $\times$ *Crisis*. Moreover, the interaction term *Large Non-Bank* $\times$ *Crisis* has the expected negative sign but is not statistically significant.

Third, I proxy for the funding constraints of the sponsors based on their CDS spreads during the last quarter of 2019. This limits my sample to only bank-sponsored funds. I sort bank sponsors into two categories based on the median CDS spreads. The baseline category consists of funds sponsored by banks with above median CDS spreads. The results reported under column 4 of Table 1.8 show that the interaction term *Low CDS* $\times$ *Crisis* has the expected negative sign but is not statistically significant, likely due to the reduction in the sample size.

Overall, the results based on alternative proxies of sponsor financial strength provide additional support for the baseline finding where funds affiliated with financially strong intermediaries suffer higher investor redemptions during the crisis.

1.6.3 Excluding sponsor support funds

Some US-based institutional prime funds received support from their sponsors during the Covid crisis. These were all bank-sponsored funds, and the sponsors collectively injected USD 3.2 billion to purchase the long-dated securities of their respective funds to bolster the funds' weekly liquidity profile.[17] Since these funds experienced extraordinary redemptions that could potentially skew my results, I exclude them from the sample. The results reported in Table 1.9 show that my baseline result is robust to excluding funds that received sponsor support. The coefficient estimate on *Bank* $\times$ *Crisis* continues to be negative and statistically significant across all specifications, although the economic magnitude has expectedly decreased.

[INSERT TABLE 1.9]

1.7 Conclusion

Sponsor support is an important and unique feature of the US MMF regulatory framework. It can help restore investor confidence in the fund's ability to uphold its value and prevent a

[17] These include the Dreyfus Cash Management Fund, sponsored by Bank of New York Mellon, and the Goldman Sachs Financial Square MMF and Goldman Sachs Financial Square Prime Obligations Fund, sponsored by Goldman Sachs.

system-wide run on MMFs during periods of acute market stress. However, it can also give rise to a moral hazard, where MMFs affiliated with deep-pocketed sponsors may engage in higher risk-taking. This, combined with the discretionary nature of sponsor support, introduces uncertainty regarding the ultimate bearer of risk in the event of extreme market volatility. Given these trade-offs, the utility of sponsor support for MMFs' stability remains an empirical question.

This paper sheds light on this important policy issue by examining the run on institutional prime MMFs during the Covid crisis of March 2020. I show that MMFs sponsored by financially strong intermediaries target a more sophisticated investor base and hold a greater share of risky securities in the period leading up to the crisis. These results provide suggestive evidence in favor of the moral hazard hypothesis. Moreover, I document a robust negative relation between the sponsor financial strength and the redemption behavior of its affiliate MMFs over the crisis period. This suggests that investors do not deem the implicit insurance offered by strong sponsors as credible and run more intensely.

The results raise important questions regarding the financial stability implications of sponsor support. These concerns are also highlighted in a recent report by the President Working Group on financial markets (President's Working Group on Financial Markets, 2020). It notes that the uncertainty associated with the discretionary nature of sponsor support could contribute to financial fragility. Among the various policy recommendations, it proposed to make sponsor support explicit for MMFs. Essentially, mandatory sponsor support is akin to the federal deposit insurance available to depository institutions. The support guarantee could mitigate investors' incentives to redeem in a stress event and, at the same time, strengthen sponsors' incentives to discipline the risk profile of the fund. However, an explicit support guarantee would impose higher costs on fund sponsors. If these costs are transferred to investors, for instance, through higher fees, it could compromise the appeal of MMFs and shrink the size of the industry, with potentially adverse effects for the wholesale funding market. Legislating sponsor support is an important policy issue, and this study offers useful insights that complement the discourse on the utility of sponsor support for MMFs.

1.8 Tables and Figures

Table 1.1: Summary statistics

This table presents summary statistics for institutional prime funds domiciled in the US under Panel A and EU under Panel B over the pre-crisis period (January - February 2020). The second column reports statistics for the complete sample of funds in each jurisdiction. The third and fourth columns report statistics for bank and non-bank-affiliated funds, respectively. The fifth column reports the difference in means across bank and non-bank funds. *safe* corresponds to the share of fund AUM invested in treasury and agency debt including repos backed by treasury and agency collateral, *risky* denotes the share of fund AUM invested in commercial paper and certificate of deposits. Cross-sectional standard deviations are reported in parentheses. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively

	All	**Bank**	**Non-Bank**	**Difference**
A. US Funds				
Assets under Management ($ Bn.)	8.44	10.73	5.51	5.22
	(12.59)	(15.26)	(7.53)	
Safe Assets (%)	17.79	13.20	23.69	-10.49***
	(9.66)	(8.46)	(7.88)	
Risky Assets (%)	65.49	69.83	59.90	9.93*
	(14.01)	(11.11)	(15.70)	
Expense Rate (%)	0.16	0.14	0.19	-0.04
	(0.08)	(0.04)	(0.11)	
Minimum Investment Amount ($ Mn.)	31.99	56.35	2.18	54.17***
	(66.84)	(83.42)	(3.46)	
Gross 7-Day Yield (%)	1.82	1.83	1.81	0.02
	(0.05)	(0.03)	(0.06)	
Daily Liquid Assets (%)	31.79	30.91	32.91	-2.00
	(5.97)	(5.84)	(6.17)	
Weekly Liquid Assets (%)	43.42	42.09	45.12	-3.03
	(6.19)	(3.83)	(8.16)	
Weighted Asset Maturity (days)	29.85	30.32	29.25	1.07
	(6.83)	(5.35)	(8.55)	
Weighted Average Life (days)	69.78	73.41	65.11	8.30
	(17.29)	(10.53)	(22.94)	
Age	20.11	18.31	22.42	-4.11
	(11.70)	(11.12)	(12.43)	
Number of Funds	32	18	14	
B. EU Funds				
Assets under Management ($ Bn.)	16.96	19.73	12.45	7.28
	(23.67)	(26.70)	(18.48)	
Safe Assets (%)	13.12	15.28	10.16	5.11
	(22.31)	(28.81)	(8.77)	
Risky Assets (%)	79.27	77.45	81.78	-4.33
	(23.76)	(30.37)	(11.01)	
Expense Rate (%)	0.17	0.14	0.22	-0.08
	(0.10)	(0.06)	(0.14)	
Minimum Investment Amount ($ Mn.)	59.72	84.90	13.55	71.36
	(129.98)	(156.84)	(30.17)	
Gross 7-Day Yield (%)	1.84	1.83	1.87	-0.04
	(0.06)	(0.07)	(0.04)	
Daily Liquid Assets (%)	27.76	28.77	24.74	4.02
	(9.09)	(10.01)	(5.97)	
Weekly Liquid Assets (%)	40.89	41.89	38.41	3.47
	(10.16)	(11.84)	(3.90)	
Weighted Asset Maturity (days)	36.76	34.88	39.81	-4.93
	(8.56)	(10.06)	(4.32)	
Weighted Average Life (days)	67.77	68.22	67.04	1.19
	(18.28)	(19.35)	(17.66)	
Age	18.80	17.65	20.64	-3.00
	(6.22)	(4.87)	(8.08)	
Number of Funds	21	13	8	

Table 1.2: Sponsor strength and risk-taking

The following regression examines the relationship between risk-taking behavior and the strength of sponsor for the cross-section of institutional prime funds. The sample spans from the begining of January 2020 to February 2020. Panel A shows the results for US-based prime funds and panel B shows the results for EU-based prime funds. In the first column, the dependent variable is the month-end percent of safe assets in fund portfolio, proxied by holdings of treasury and agency debt as well as repos collateralized by these securities. In the second column, the dependent variable is the logarithm of minimum investment amount required to invest in the fund. *Bank* is a dummy variable that is equal to one for bank-affiliated MMFs and zero otherwise. t-statistics reported in paranthesis are based on robust standard errors. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively.

	Portfolio Risk	Investor Risk
A: US Funds		
Bank	−8.78***	2.33**
	[−3.03]	[2.15]
log(Asset)	−0.11	1.33***
	[−0.11]	[3.82]
log(Minimum Investment Amount)	−0.60	
	[−1.34]	
Safe Assets		−0.08
		[−1.33]
Weighted Asset Maturity	−0.09	−0.07
	[−0.51]	[−0.99]
Age	−0.34**	−0.16***
	[−2.56]	[−2.94]
Intercept	33.01***	4.83
	[5.38]	[1.41]
Observations	32	32
Adjusted R^2	0.40	0.57

B: EU Funds		
Bank	14.54	1.25
	[1.13]	[1.37]
log(Asset)	−7.63	0.40
	[−1.38]	[0.95]
log(Minimum Investment Amount)	−1.97	
	[−1.20]	
Safe Assets		−0.02
		[−1.33]
Weighted Asset Maturity	1.94	0.07
	[1.78]	[0.83]
Age	−0.86	−0.30***
	[−1.01]	[−3.73]
Intercept	−35.78	2.85
	[−1.32]	[1.05]
Observations	17	17
Adjusted R^2	0.003	0.33

Table 1.3: Sponsor strength and run on US-based prime MMFs

The following regression compares flows across bank and non-bank-affiliated institutional prime funds based in the US during the Covid crisis episode. The sample spans from the beginning of February to March 20, with *Crisis* equal to one from March 6 to March 20. *Bank* is a dummy variable equal to one for bank-affiliated funds and zero otherwise. The dependent variable is the daily percentage change in fund AUM and is winsorized at the 0.05% and 99.5% levels. Controls include one-day lagged flow, two-day lagged weekly liquid assets, one-day lagged gross seven-day yield, one-day lagged logarithm of fund size, month-end fraction of safe holdings (treasury and agency debt as well as repos collateralized by these securities) and risky holdings (bank obligations), the logarithm of minimum investment amount, and fund age. t-statistics are reported in parenthesis. Standard errors are two-way clustered at the fund and day levels. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)
Bank	0.38*	0.38*		0.67**	
	[1.80]	[1.72]		[2.24]	
Crisis	−0.96				
	[−1.44]				
Bank x Crisis	−2.21***	−2.21***	−2.20***	−1.98***	−1.96***
	[−3.05]	[−2.93]	[−2.89]	[−3.10]	[−3.06]
Intercept	−0.30				
	[−1.36]				
Day FE	No	Yes	Yes	Yes	Yes
Fund FE	No	No	Yes	No	Yes
Controls	No	No	No	Yes	Yes
Bank Funds	18	18	18	18	18
Non-bank Funds	14	14	14	14	14
Observations	1,084	1,084	1,084	1,008	1,008
Adjusted R^2	0.08	0.16	0.16	0.16	0.17

Table 1.4: Sponsor strength and run on EU-based prime MMFs

The following regression compares flows across bank and non-bank-affiliated institutional prime funds based in the EU during the Covid crisis episode. The sample spans from the beginning of February to March 20, with *Crisis* equal to one from March 6 to March 20. *Bank* is a dummy variable equal to one for bank-affiliated funds and zero otherwise. The dependent variable is the daily percentage change in fund AUM and is winsorized at the 0.05% and 99.5% levels. Controls include one-day lagged flow, two-day lagged weekly liquid assets, one-day lagged gross seven-day yield, one-day lagged logarithm of fund size, month-end fraction of safe holdings (treasury and agency debt as well as repos collateralized by these securities) and risky holdings (bank obligations), the logarithm of the minimum investment amount, and fund age. t-statistics are reported in parenthesis. Standard errors are two-way clustered at the fund and day levels. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)
Bank	0.14	0.14		−2.13**	
	[1.19]	[1.01]		[−2.28]	
Crisis	−0.75				
	[−0.92]				
Bank x Crisis	−0.47	−0.47	−0.47	−0.51	−0.59
	[−0.42]	[−0.41]	[−0.41]	[−0.53]	[−0.75]
Intercept	−0.03				
	[−0.29]				
Day FE	No	Yes	Yes	Yes	Yes
Fund FE	No	No	Yes	No	Yes
Controls	No	No	No	Yes	Yes
Bank Funds	13	13	13	8	8
Non-bank Funds	8	8	8	4	4
Observations	714	714	714	341	341
Adjusted R^2	0.01	0.01	0.004	0.10	0.14

Table 1.5: Pre-trend analysis

The following regression tests for pre-trends in the daily flows of bank and non-bank-affiliated institutional prime funds based in the US. The sample spans from the beginning of February until the 20th of March, with *Crisis* equal to one from March 6 to March 20. The $Crisis_t$ are indicators for the different weeks t before the start of the crisis, and the baseline period is the last week before the crisis. *Bank* is a dummy variable equal to one for bank-affiliated funds and zero otherwise. The dependent variable is the daily percentage change in fund AUM and is winsorized at the 0.05% and 99.5% levels. Controls include one-day lagged flow, two-day lagged weekly liquid assets, one-day lagged gross seven-day yield, one-day lagged logarithm of fund size, month-end fraction of safe holdings (treasury and agency debt as well as repos collateralized by these securities) and risky holdings (bank obligations), the logarithm of minimum investment amount, and fund age. t-statistics are reported in parenthesis. Standard errors are two-way clustered at the fund and day levels. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)
Bank	0.91^{*}	0.93^{*}
	[1.73]	[1.92]
Crisis_{-1}	-1.49^{**}	
	[−1.98]	
Crisis_{-2}	−0.52	
	[−1.39]	
Crisis_{-3}	−0.56	
	[−1.28]	
Crisis_{-4}	-0.73^{*}	
	[−1.66]	
Crisis	-1.21^{**}	
	[−2.03]	
Bank x Crisis_{-1}	−0.72	−0.81
	[−0.80]	[−0.81]
Bank x Crisis_{-2}	0.23	0.15
	[0.53]	[0.35]
Bank x Crisis_{-3}	−0.03	−0.13
	[−0.08]	[−0.41]
Bank x Crisis_{-4}	0.03	−0.10
	[0.05]	[−0.22]
Bank x Crisis	-2.14^{**}	-2.23^{**}
	[−2.55]	[−2.61]
Intercept	0.98	
	[0.46]	
Day FE	No	Yes
Controls	Yes	Yes
Bank Funds	18	18
Non-bank Funds	14	14
Observations	1,098	1,098
Adjusted R^2	0.11	0.16

Table 1.6: Sponsor strength, risk-taking and run-risk

The following table reports results of a two-stage regression based on the sample of US-based institutional prime funds. Panel A shows the results for the first-stage logistic regression on the cross-section of funds. The dependent variable is a dummy equal to one for bank-affiliated funds and zero otherwise. *Safe* is the fraction of safe asset holdings (treasury and agency debt and repos collateralized by these securities). *Min. investment amount* is the logarithm of the minimum investment amount required by the fund. *Assets* is the total assets under management of the fund. Each variable is averaged over the period January-February. Panel B shows the results for the second-stage panel regression where the dependent variable is the daily percentage change in fund AUM, winsorized at the 0.05% and 99.5% levels, over the crisis period from March 6 until March 20. $\widehat{Prob(Bank)}$ are the fitted probabilities from the first-stage regression. Other controls include one-day lagged flow, two-day lagged weekly liquid assets, one-day lagged gross seven-day yield, one-day lagged logarithm of fund size, and fund age. z-statistics and t-statistics reported in parenthesis are based on robust standard errors under Panels A and B, respectively. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively.

A: First stage - dependent variable bank-affiliation indicator	
Safe Assets	-0.09^{*}
	[−1.69]
log(Min. Investment Amount)	0.71^{***}
	[2.99]
Intercept	1.06
	[0.99]
Observations	32
p-value: wald test	0.02

B: Second stage - dependent variable daily % change in fund AUM	
$\widehat{\text{Prob(Bank)}}$	-1.61^{**}
	[−2.05]
$\log(\text{Asset}_{t-1})$	-0.31^{*}
	[−1.77]
Weekly Liquid Assets_{t-2}	0.06
	[1.32]
Gross 7-Day Yield_{t-1}	−0.83
	[−0.70]
Flow_{t-1}	0.22^{***}
	[2.98]
Age	−0.04
	[−1.43]
Day FE	Yes
Observations	256
Adjusted R^2	0.23

Table 1.7: Alternative channel

The following regression tests for the alternative channel that could amplify redemption pressure on US-based institutional prime funds over the crisis period. The sample spans from the beginning of February to March 20, with *Crisis* equal to one from March 6 to March 20. *Bank* is a dummy variable equal to one for bank-affiliated funds and zero otherwise. The dependent variable is the daily percentage change in fund AUM and is winsorized at the 0.05% and 99.5% levels. *WLA* is the two-day lagged weekly liquidity level of the fund. Controls include one-day lagged flow, two-day lagged weekly liquid assets, one-day lagged gross seven-day yield, one-day lagged logarithm of fund size, month-end fraction of safe holdings (treasury and agency debt and repos collateralized by these securities) and risky holdings (bank obligations), the logarithm of minimum investment amount, and fund age. t-statistics are reported in parenthesis. Standard errors are two-way clustered at the fund and day levels. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively.

	(1)
WLA	-0.08^{*}
	[−1.99]
Bank	0.56^{**}
	[2.28]
WLA x Crisis	0.14^{**}
	[2.26]
Bank x Crisis	-1.60^{***}
	[−2.78]
Day FE	Yes
Controls	Yes
Bank Funds	18
Non-bank Funds	14
Observations	1,008
Adjusted R^2	0.17

Table 1.8: Alternate proxies for sponsor financial strength

The following regression compares flows across US-based institutional prime funds based on various proxies for sponsor financial strength over the Covid crisis period. The sample spans from the beginning of February to March 20, with *Crisis* equal to one from March 6 to March 20. The dependent variable is the daily percentage change in fund AUM and is winsorized at the 0.05% and 99.5% levels. The first two columns characterize fund sponsors based on their G-SIB status as of the end of 2019. *GSIB* is a dummy equal to one for funds sponsored by G-SIBs and is zero otherwise. The third column characterizes fund sponsors based on their total assets as of the end of 2019. *Large-nonbank* is a dummy equal to one for funds sponsored by non-banks with above median assets, *Small-bank* is a dummy equal to one for funds sponsored by banks with below median assets, and *Large-bank* is a dummy equal to one for funds sponsored by banks with above median assets. The baseline group comprises of funds sponsored by non-banks with below median assets. The fifth column characterizes fund sponsors based on their average daily CDS spreads as of the last quarter of 2019. *Low CDS* is a dummy equal to one for funds sponsored by banks with below median CDS spreads, and is zero otherwise. The control variables are defined in Table 3. t-statistics are reported in parenthesis. Standard errors are two-way clustered at the fund and day levels. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively.

	GSIB	GSIB	Assets	CDS
Non-GSIB	0.32	−0.43		
	[1.19]	[−1.31]		
GSIB × Crisis	−1.83**	−0.86		
	[−2.41]	[−0.84]		
Large Non-bank			0.58	
			[1.31]	
Small Bank			1.70***	
			[3.94]	
Large Bank			1.35**	
			[2.44]	
Large nonbank × Crisis			−0.19	
			[−0.17]	
Small Bank× Crisis			−2.18**	
			[−2.31]	
Large Bank × Crisis			−2.54***	
			[−2.91]	
Low CDS				0.72
				[1.30]
Low CDS × Crisis				−0.30
				[−0.26]
Day FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
GSIB Funds	14	14		
Non-GSIB Funds	18	4		
Small Non-bank Funds			4	
Large Non-bank Funds			6	
Small Bank Funds			6	
Large Bank Funds			12	
Low CDS Funds				8
High CDS Funds				7
Observations	1,008	563	882	467
Adjusted R^2	0.16	0.29	0.18	0.27

Table 1.9: Excluding funds with sponsor support during the crisis

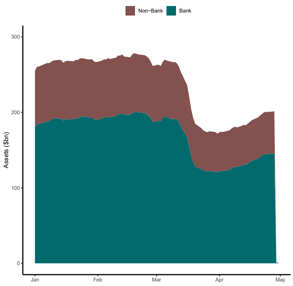
The following regression compares flows across bank and non-bank-affiliated institutional prime funds based in the US, excluding those that received sponsor support during the Covid crisis episode. The sample spans from the beginning of February to March 20, with *Crisis* equal to one from March 6 to March 20. *Bank* is a dummy variable that is equal to one for bank-affiliated funds and zero otherwise. The dependent variable is the daily percentage change in fund AUM and is winsorized at the 0.05% and 99.5% levels. Controls include one-day lagged flow, two-day lagged weekly liquid assets, one-day lagged gross seven-day yield, one-day lagged logarithm of the fund size, month-end fraction of safe holdings (treasury and agency debt and repos collateralized by these securities) and risky holdings (bank obligations), the logarithm of the minimum investment amount, and fund age. t-statistics are reported in parenthesis. Standard errors are two-way clustered at the fund and day levels. ***, **, * represent 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)
Bank	0.34*	0.33		0.58*	
	[1.65]	[1.56]		[1.84]	
Crisis	−0.96				
	[−1.44]				
Bank x Crisis	−1.62***	−1.62**	−1.61**	−1.48**	−1.50***
	[−2.62]	[−2.50]	[−2.46]	[−2.68]	[−2.84]
Intercept	−0.30				
	[−1.36]				
Day FE	No	Yes	Yes	Yes	Yes
Fund FE	No	No	Yes	No	Yes
Controls	No	No	No	Yes	Yes
Bank Funds	15	15	15	15	15
Non-bank Funds	14	14	14	14	14
Observations	982	982	982	912	912
Adjusted R^2	0.05	0.11	0.12	0.12	0.13

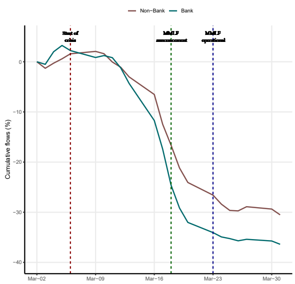
Figure 1.1: Prime MMFs during the Covid crisis

The figure summarizes the Covid run on institutional prime funds domiciled in the US and EU. The left panel displays the daily total assets (in billions of dollars) from January to April 2020. The center panel plots the percentage cumulative flow from the beginning until the end of March 2020. The dashed red line marks the beginning of the crisis, the dashed green line denotes the announcement of the Fed money market liquidity facility (MMLF), and the dashed blue line points to the date when MMLF was operationalized. The right panel depicts the distribution densities of cumulative flows between bank and non-bank funds over March 1-20.

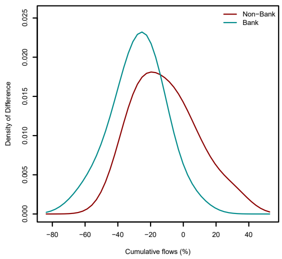
A. US Funds



TNA (Bn.)

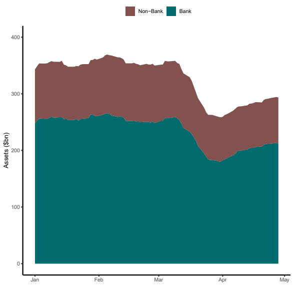


Cumulative flows(%)

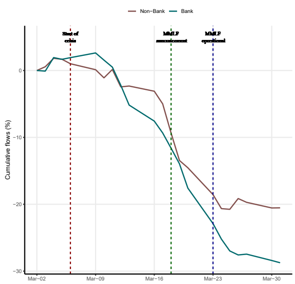


Distribution densities of cumulative flows

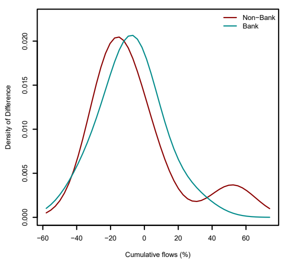
B. EU Funds



TNA (Bn.)



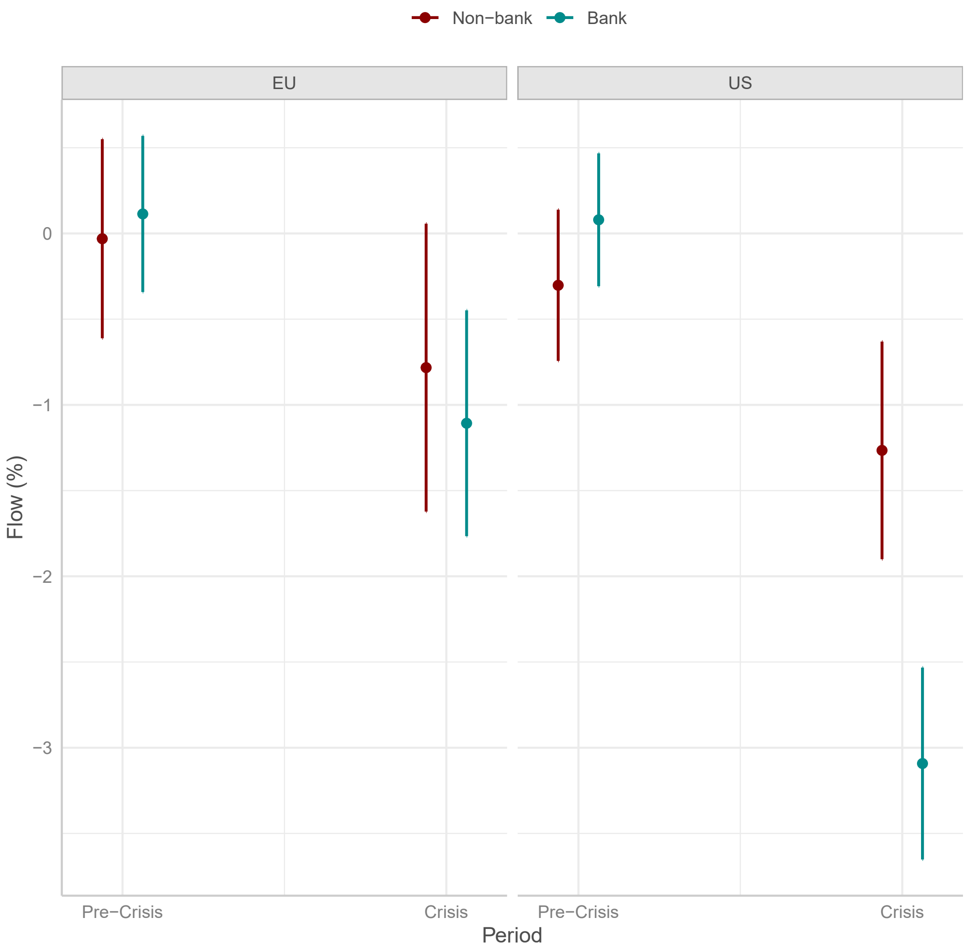
Cumulative flows(%)



Distribution densities of cumulative flows

Figure 1.2: Average daily change in fund assets

This figure shows the average daily percentage change in the total assets of institutional prime funds. The panels on the left and right show the change for EU and US-domiciled funds, respectively. The blue error bar denotes bank-affiliated funds, and the red error bar denotes non-bank-affiliated funds. The pre-crisis period starts from the beginning of February until the 5th of March, and the crisis period starts from the 6th until the 20th of March.



1.A Additional Tables

Table A1: Regulatory features of US and EU prime MMFs

The following table compares the regulatory features of prime MMFs domiciled in the US and EU based on the MMF reforms introduced in each jurisdiction after the great financial crisis. For US-based prime funds, the focus is on funds marketed to institutional investors. For EU-based prime funds, the focus is on low-volatility net-asset-value funds.

	US prime funds	**EU prime funds**
Introduction	July 2014	June 2017
Implementation	October 2016	Funds existing prior to July 2017 need to comply by January 2019. Newly established funds must comply by July 2018.
Maximum WAM	60 days	60 days
Maximum WAL	120 days	120 days
Minimum WLA	30%	30%
Minimum DLA	10%	10%
Mandatory fees & gates	Minimum 1% liquidity fee if WLA < 10%	Up to 3% liquidity fees or up to 15 days gating if WLA < 10%
Discretionary fees & gates	Up to 2% liquidity fee and/or 10-days gating if WLA < 30%	Liquidity fees and/or up to 15 days gating if WLA < 30% & daily net redemptions exceed 10%
Valuation method	Mark-to-market	Amortized cost
NAV	Floating	Constant
Sponsor support	Allowed	Not allowed
Concentration limits	5% per issuer	5% per issuer
Disclosure requirement	Daily disclosure of fund liquidity and NAV	Daily disclosure of fund liquidity and shadow NAV

Table A2: Internal prime funds in the US

The following table lists US-based institutional prime funds that are available exclusively to affiliates within the fund complex. The reported assets are in USD billion as of the end of January 2020.

Fund	**Assets**
American Funds Central Cash	104.89
BlackRock Cash Instit MM	52.26
Columbia Short-Term Cash Fund	16.20
DFA Short Term Investment	13.28
Fidelity Cash Central	43.34
Fidelity Money Market Central	1.72
Fidelity Sec Lending Cash Central	19.83
JPMorgan Sec Lending Money Market	3.45
PGIM Inst Money Market	17.11
UBS Limited Purpose Cash Inv Fund	3.89
Vanguard Market Liquidity Fund	67.23

Table A3: Prime fund sponsors

The following table lists the identities of sponsors with publicly offered institutional prime funds in the US and EU. The reported assets are in USD billion as of the end of January 2020.

Sponsor	**Bank Holding Company**	**US**		**EU**	
		Funds	Assets	Funds	Assets
JPMorgan	Yes	1	64.62	2	92.11
Goldman Sachs	Yes	2	26.00	1	60.24
BlackRock	No	3	23.51	1	56.31
Morgan Stanley	Yes	3	18.40	1	24.84
SSgA	Yes	2	24.12	1	14.66
HSBC	Yes	0	0.00	1	35.14
Federated	No	2	27.23	1	3.07
Fidelity	No	2	18.87	1	7.57
Western	No	1	2.75	2	22.09
BNY Mellon	Yes	2	15.56	2	8.47
UBS	Yes	1	20.17	1	3.16
Northern	Yes	1	4.05	1	11.29
Deutsche	Yes	1	0.51	1	11.26
Wells Fargo	Yes	2	11.10	0	0.00
Invesco	No	2	3.18	1	7.59
Schwab	Yes	1	5.45	0	0.00
Aberdeen Standard	No	0	0.00	1	2.59
LGIM	No	0	0.00	1	1.96
First American	Yes	1	1.27	0	0.00
BNP Paribas	Yes	0	0.00	1	1.00
Amundi	Yes	0	0.00	1	0.94
BMO	Yes	1	0.53	0	0.00
Meeder	No	1	0.36	0	0.00
MainStay	No	1	0.35	0	0.00
PIF	No	1	0.20	0	0.00
T Rowe Price	No	1	0.12	0	0.00

Chapter 2

Dealer Networks and Cost of Immediacy

Jens Dick-Nielsen, Copenhagen Business School

Thomas Kjær Poulsen, BI Norwegian Business School

Obaidur Rehman, BI Norwegian Business School

Abstract

We examine how dealer network position affects transaction costs when dealers provide immediacy by taking bonds into inventory. Dealers with central network positions provide more immediacy and revert deviations from their desired inventory faster than peripheral dealers do. The cost of immediacy decreases with centrality for customer trades (centrality discount) and increases with centrality for interdealer trades (centrality premium). These findings support recent network models in which central dealers have a comparative advantage in managing inventory. We isolate the inventory management channel and avoid confounding effects from adverse selection and heterogeneous customer clienteles by using trades around bond index exclusions.

2.1 Introduction

The dealer network in many over-the-counter (OTC) markets exhibits a core-periphery structure. Core dealers are highly interconnected and account for most of the trading activity relative to peripheral dealers who are less connected. Identifying how network structure affects transaction costs is important for understanding price formation and liquidity provision in OTC markets. The empirical literature disagrees on the sign of the centrality spread within and across OTC markets, i.e., whether trading at the core is more expensive than at the periphery. In the corporate bond market, Di Maggio et al. (2017) and Hollifield et al. (2020) find a centrality premium, whereas Goldstein and Hotchkiss (2020) find a centrality discount.[1] The theoretical literature can rationalize the existence of either a centrality premium or a discount depending on which economic channel dominates the price formation.[2] Our contribution is to empirically identify the effect of a specific and important economic channel—the inventory management channel.

The inventory management channel describes that dealers with wider trading networks are better able to manage inventory risk (see e.g., Huang and Wei (2017), Üslü (2019), and Colliard et al. (2021)). We exploit a unique trading environment for corporate bonds to isolate this channel. When bonds exit the Bloomberg Barclays US Corporate Bond Index, index trackers have a strong desire to sell excluded bonds in order to minimize the tracking error. This urgency to trade close to the exclusion date compels index trackers to demand immediacy from dealers. Dealers then provide immediacy by taking bonds into inventory and use their trading network to manage inventory risk.

We can isolate the effect of inventory risk and dealer network position on transaction costs because the index exclusion setting avoids confounding effects from adverse selection and heterogeneous customer clienteles. Mechanical index rules make exclusions information-free events, and the desire to minimize tracking error renders index trackers a price-inelastic customer clientele that repeatedly interacts with dealers. We provide evidence that bond funds managed by the largest global asset managers are the dominant sellers of excluded bonds close to the exclusion date. This highly concentrated customer clientele likely has minimal heterogeneity in terms of sophistication or outside options. We focus on index exclusions for identification but find similar results for the entire corporate bond market. The inventory management channel is, therefore, potentially the dominating channel also for the average transaction in the market.

We document a centrality discount when index trackers (the sellers) request immediacy from dealers (the buyers) close to the exclusion date and when dealers sell off their newly acquired inventory to customers after exclusion. The economic magnitude is sizeable, with a one standard deviation increase in dealer centrality corresponding to a decrease of 6–11% of

[1] Li and Schürhoff (2019) and Hasbrouck and Levich (2021) find a centrality premium in markets for municipal bonds and foreign exchange, whereas Hollifield et al. (2017) find a centrality discount for securitized debt.

[2] See, e.g., Huang and Wei (2017), Babus and Kondor (2018), Wang (2018), Li and Song (2019), Neklyudov (2019), Üslü (2019), Hugonnier et al. (2020), Li and Song (2020), Shen et al. (2020), Colliard et al. (2021), and Sambalaibat (2022).

the mean and 15–25% of the median bid-ask spread. When dealers trade index-excluded bonds with each other, we find an interdealer centrality premium. These findings support the inventory management channel according to which core dealers have a comparative advantage in carrying inventory. Core dealers derive market power from their network position and, therefore, trade at more favorable interdealer prices (i.e., they charge higher transaction costs to other dealers). Since core dealers can unwind inventory at more favorable interdealer prices, they can offer their customers better prices (i.e., lower transaction costs) than peripheral dealers. When competitive dealers extract maximal rent from index trackers, prices across dealers only reflect the cost of providing immediacy.

Before we measure the cost of immediacy, we present three additional results to corroborate the inventory management channel. First, we confirm that dealers provide immediacy by using their inventories and unwind part of their newly acquired inventory in the interdealer network. The inventory buildup peaks on the exclusion date and is at least three to four times higher for core dealers than for peripheral dealers. Second, core dealers unwind their newly acquired inventory substantially faster than peripheral dealers do. The cumulative change in inventories after the exclusion date and our analysis of the dealer-specific speed of inventory adjustment demonstrate this feature. Third, peripheral dealers are more likely to buy index-excluded bonds when core dealers have higher inventory buildup and therefore may face inventory constraints. These findings suggest that core dealers have a comparative advantage in carrying inventory.

The inventory management channel affects the centrality spread for those trades only where dealers use their inventory. In a prearranged trade, the dealer acts as a broker by matching buyers and sellers without taking inventory risk. We follow Friewald and Nagler (2019) and use prearranged trades as a proxy for aversion to inventory risk. We find that peripheral dealers, on average, prearrange 11–17% of their trading volume compared to 5–10% for core dealers. Core dealers are therefore more willing to use their inventory to provide immediacy consistent with the inventory management channel. When dealers prearrange trades between customers, the centrality spread is statistically insignificant from zero, consistent with dealers not taking any inventory risk. When dealers use the interdealer network in a prearranged trade, we find a centrality discount. This finding reflects that prearranging dealers with central network positions trade at more favorable interdealer prices and pass on some of this benefit to customers.

After the 2007–2009 financial crisis, we observe that core dealers account for more trading activity and that dealers become better connected in the interdealer network. These findings are consistent with post-crisis regulatory reforms increasing the cost of holding inventory. Higher inventory costs increase the comparative advantage of core dealers in managing inventory and the incentive for dealers to become better connected. We show that the centrality spread is typically less pronounced after the crisis, consistent with an increase in network density, reducing the connection asymmetry between dealers.

Our results broadly support recent models of trading in OTC markets with network frictions and inventory risk (Huang and Wei (2017), Üslü (2019), and Colliard et al. (2021)). In these models, dealers use the interdealer network to unwind inventory. Core dealers are better connected and, therefore, have a comparative advantage in managing inventory.

Huang and Wei (2017) assume that dealers compete to offer the best price to win a customer order before distributing their inventories through bilateral trading with directly connected dealers. The core-periphery structure creates market power for dealers because bilateral trading volumes affect interdealer prices. Core dealers trade at more favorable interdealer prices because they can divide their trades between a higher number of directly connected dealers. In turn, core dealers outbid peripheral dealers to win the customer order when their relative inventory is not too high. As core dealer inventories increase, they trade more in the interdealer market and move interdealer prices against them. Eventually, the higher inventory level outweighs the connection advantage, and a peripheral dealer wins the customer order. Importantly, a winning core dealer offers better prices (i.e., higher bid or lower ask) to the customer than a winning peripheral dealer does. The inventory management channel therefore predicts a customer–dealer centrality discount and an interdealer centrality premium originating from the asymmetry in dealer connections and market power in the interdealer market.[3]

Colliard et al. (2021) develop a model in which core dealers share inventory risk efficiently between each other while peripheral dealers have heterogeneous connections to the core and face bargaining frictions. Better-connected peripheral dealers gain market power from their network position relative to lesser-connected peripheral dealers. Interdealer trades may therefore reflect a centrality premium, while customer–dealer trades typically reflect a centrality discount consistent with our results.

In the search-and-bargaining model by Üslü (2019), the faster execution speed of core dealers gives a comparative advantage in carrying inventory. Core dealers are therefore less averse to inventory risk and charge lower transaction costs to customers. Faster execution speed, however, also enables core dealers to extract more surplus when bargaining with (slower) peripheral dealers. This speed premium predicts that interdealer transaction costs increase with dealer centrality consistent with our results. The model features either a centrality premium or a discount depending on whether the speed premium or inventory aversion dominates, but in any case, faster execution speed enables core dealers to dominate the trading relationship. Taken together, the mechanism that results in the centrality spread originates from the common feature of inventory holding costs in Huang and Wei (2017), Üslü (2019), and Colliard et al. (2021).

We conduct several tests to rule out confounding effects in the index exclusion setting. First, adverse selection models such as Babus and Kondor (2018) predict a centrality discount because core dealers observe more order flow and therefore face less adverse selection. Adverse selection is unlikely to explain our centrality spread because mechanical index rules, not information, dictate the decision to trade. Our estimate of the centrality spread from transaction prices of the

[3]In the Appendix, we show how the customer–dealer centrality discount and interdealer centrality premium arises in the Huang and Wei (2017) model. We use this model for its simplicity to illustrate the inventory management channel instead of the richer models by Üslü (2019) and Colliard et al. (2021).

same bond at the same time across dealers also absorbs all time-varying bond and issuer-specific information.

Second, search-based models with heterogeneous customer clienteles predict either a centrality premium or a discount for customer–dealer trades. These models feature a customer clientele segmented on the need for execution speed. Li and Schürhoff (2019) predict a centrality premium when customers trade off execution speed against cost. Fast-preference customers trade with core dealers that offer fast execution at a higher cost. Our centrality spread does not reflect this trade-off because index trackers request immediacy and do not pursue alternative trading arrangements. Hollifield et al. (2017) predict a centrality discount because the fast execution offered by core dealers attracts customers with stronger outside options. Sambalaibat (2022) also predicts a centrality discount when core dealers specialize in fast-preference customers with frequent trading needs (e.g., index trackers) and peripheral dealers specialize in slow-preference customers with infrequent trading needs (e.g., pension funds). One concern is, therefore, that several customer clienteles could sell excluded bonds close to the exclusion date or that there could be heterogeneity within the clientele of index trackers.

We use data from several sources to investigate customer heterogeneity because our bond transactions data from TRACE do not include customer identities. Changes in institutional bond holdings around the exclusion date reveal that bond funds and insurance companies collectively account for more than 90% of the implied sell volume for excluded bonds. The NAIC bond transactions data show that insurance companies almost exclusively trade away from the exclusion date. In contrast, the implied sell volume from bond funds aligns well with the actual customer sell volume at exclusion. This customer clientele is highly concentrated, with the top 10 fund families—some of the largest global asset managers—accounting for nearly the entire sell volume. We use the number of implied sellers and the dispersion in seller size to measure customer heterogeneity. In our most restrictive setting, we remove trades that could involve customers other than bond funds and document a centrality discount for excluded bonds sold by a single fund family only. These findings suggest that customer heterogeneity is unlikely to explain the centrality spread for index exclusions.

Our results also help reconcile the mixed empirical evidence on the centrality spread in the corporate bond market. Di Maggio et al. (2017) find a centrality premium for interdealer trades but no significant centrality spread for customer–dealer trades. Their centrality spread is derived from trades executed within at most 1 hour of each other. Since these trades carry little inventory risk, their results cannot directly identify the effect of inventory risk management. Hollifield et al. (2020) find a centrality premium using spreads computed when a dealer buys from a customer and sells to either a customer or another dealer. Goldstein and Hotchkiss (2020) find a centrality discount without conditioning on counterparty type (dealer versus customer). Our findings of a centrality discount for customer–dealer trades and a centrality premium for interdealer trades suggest that the sample used by Goldstein and Hotchkiss (2020) is likely tilted more towards customer–dealer trades than interdealer trades.[4] Finally, Di Maggio et al. (2017), Hollifield et al. (2020), and Goldstein and Hotchkiss (2020) consider the cross-section of all trades where it is not clear a priori, which channel dominates in determining the centrality spread. In contrast, we identify information-free trades by price-inelastic index trackers where dealers provide immediacy and use their network position to manage inventory risk. By doing so, we can uniquely identify inventory risk as an important channel for determining transaction costs in a network structure.

2.2 Corporate Bond Index Tracking

We consider monthly exclusions from the Bloomberg Barclays US Corporate Bond Index (previously called the Lehman Corporate Bond Index and the Barclay Capital Corporate Bond Index) similar to Dick-Nielsen and Rossi (2019) and Ottonello (2019). The sample period is from July 2002 to August 2018. The index includes all US investment grade corporate bonds with more than one year to maturity in addition to several other requirements.[5] Index-eligible bonds account for a large fraction of the US corporate bond market. The index is rebalanced at 3 PM EST on the last trading day of each month. Importantly, the rules for bonds entering or exiting the index are fully transparent and available to all market participants. Bonds enter the index for two main reasons: (1) they are newly issued and satisfy the index requirements, or (2) they are upgraded from speculative to investment grade. Bonds exit the index for three main reasons: (1) the remaining time to maturity drops below one year, (2) they are downgraded from investment grade to speculative grade, or (3) they are called by the issuer. We focus on maturity exclusions and downgrade exclusions.[6]

Unlike equity index trackers that hold a fraction of each stock in the index, bond index trackers instead follow a sampling strategy. They invest only in a fraction of index-eligible bonds to match their portfolio on duration, cash flows, quality, and callability to that of the index. Bond index trackers' objective is to minimize the tracking error between their portfolio and the index. They compete on having a low tracking error because it resolves the agency problem between outside investors and fund managers by showing the commitment to track the index. This objective creates a strong motive to trade as close as possible to index rebalancing. Dick-Nielsen and Rossi (2019) show that index trackers could, in principle, reduce transaction

[4]This observation is also consistent with how the centrality spread is calculated in Goldstein and Hotchkiss (2020). They compute spreads based on dealer round trips involving both customer–dealer and interdealer trades. We can infer from Table 4 in their paper that out of all dealer round trips, 29% are interdealer round trips, while the remaining 71% involve at least one customer trade.

[5]The most recent index requirements are described at https://data.bloomberglp.com/professional/sites/10/2017-08-08-Factsheet-US-Corporate1.pdf

[6]Dick-Nielsen and Rossi (2019) report that there is little price pressure for bond inclusions due to the sampling strategy followed by index trackers. There are only a few exclusions due to bonds being called by the issuer in our sample period.

costs by trading away from the exclusion date, but they would do so at the expense of increasing tracking error risk. Conversations with leading bond funds confirm that they sell as close as possible to the exclusion date and do not pursue alternative trading arrangements. They seek to sell within the exclusion date, but for large positions and in a more illiquid market, they start selling 1–3 days before the exclusion date to minimize execution risk.

2.3 Data

We use bond transaction data from Academic TRACE distributed by FINRA. We clean the data according to Dick-Nielsen and Poulsen (2019) and delete trades between dealers and their non-FINRA affiliates (see the Appendix for further discussion). The data contain all transactions in US corporate bonds with anonymized dealer identifiers for each transaction. This feature allows us to trace the dealer network structure and track how individual dealer inventories change over time. We use trades with a par value of at least $100,000 when computing prices, but keep all trades when computing network variables and dealer inventories.[7] We obtain bond characteristics from the Mergent Fixed Income Securities Database (FISD) and institutional bond holdings from Refinitiv eMAXX. Finally, we use bond transactions data from the National Association of Insurance Commissioners (NAIC) to identify trades by insurance companies.

[INSERT TABLE 2.1]

Table 2.1 presents summary statistics for our sample of index exclusions from July 2002 to August 2018 and for a sample of all corporate bonds. We use the latter sample of all non-convertible corporate bonds that are not rule 144A to characterize the dealer network structure. These bonds resemble the universe of index-eligible bonds. Panel A in Table 2.1 shows that most bond exclusions have transactions in TRACE. The third column reports the number of excluded bonds that dealers buy from customers at exclusion (event days -3 to 0, where event day 0 is the exclusion date). This number is lower than the total number of exclusions because index trackers follow a sampling strategy instead of holding all index-eligible bonds. The last column contains the number of excluded bonds that dealers sell to customers after exclusion (event days 1 to 30). In Panel B of Table 2.1, we present bond characteristics for each sample.

We use interdealer transactions from our sample of all corporate bonds to characterize the dealer network structure. Our main measure of dealer centrality is the eigenvector centrality score, which is also used by, for example, Hollifield et al. (2017), Li and Schürhoff (2019), and Goldstein and Hotchkiss (2020). At the end of each month, we compute dealer-level eigenvector centrality scores, which reflect both direct and indirect trading partners. This centrality measure assigns higher scores to dealers with more trading partners and to dealers with more connected

[7] We show in the Appendix that our results are robust to including all trade sizes and to using an alternative network centrality measure.

trading partners. The eigenvector centrality score is bounded between zero and one, with the most central dealer attaining a score of one.

[INSERT FIGURE 2.1]

Figure 2.1 confirms the finding by Di Maggio et al. (2017) that the dealer network in the corporate bond market has a definite core-periphery structure with a small number of highly connected dealers and a larger number of peripheral dealers. Panel A shows the distribution of eigenvector centrality scores over the entire sample period. The distribution is highly skewed towards zero meaning that most dealers are peripheral. Panel B visualizes the network structure in a single month. Each circle denotes a broker-dealer firm, the size and shade of each circle is proportional to the centrality score, and each line represents a trading relationship.

2.4 Volume and Inventory Dynamics

We now study trading volume around the exclusion date and provide evidence that bond funds are the dominant sellers of excluded bonds. We also find that it is core dealers mostly that provide immediacy to index trackers and that peripheral dealers are more likely to provide immediacy in months during which core dealers may face inventory constraints. Finally, we examine inventory dynamics around the exclusion date and document that core dealers unwind their inventory faster than peripheral dealers do.

2.4.1 Volume dynamics around index exclusions

First, we examine the evolution of average daily trading volume for customer–dealer trades and interdealer trades separately for maturity and downgrade exclusions. The event window is 100 trading days before and after the exclusion date, which is event day 0. We aggregate trading volume across all bonds excluded in a given month and scale by the total nominal size of bonds excluded in that month. For each event day, we compute the average scaled volume across months.

[INSERT FIGURE 2.2 AND TABLE 2.2]

Figure 2.2 shows a similar pattern in the average scaled volume of index-excluded bonds for both customer–dealer and interdealer trades. Trading volume begins to surge in the days immediately leading up to the exclusion date and peaks on or close to the exclusion date. In the days immediately after exclusion, there is a marked reduction in average scaled volume. For example, the average scaled volume for maturity-excluded bonds 10 days before and after the exclusion date is only 22% to 24% of that at the exclusion date for customer–dealer trades and 56% to 60% for interdealer trades. Similarly, the average scaled volume for downgrade-excluded bonds is only 32% to 28% for customer–dealer trades and 59% to 49% for interdealer trades.

The significant surge in customer trading volume close to the exclusion date shows that some customers track the index. Since index trackers cannot be certain to transact at the desired point in time they start selling a few days before the exclusion date. We therefore use an event window from event days -3 to 0 to identify customer sell trades that are most likely from index trackers. The interdealer volume also spikes around the exclusion date and remains elevated after exclusion as dealers use the interdealer network to unwind their inventory buildup.

2.4.2 Index trackers

Bond transactions data from TRACE do not have customer identities. We therefore use changes in institutional bond holdings from Refinitiv eMAXX to identify customers that sell excluded bonds from 3 months before to 2 months after the exclusion date. The quarterly reporting frequency in eMAXX allows us to measure the net sell volume of excluded bonds by customer type. The main customer types are bond funds (both mutual funds and ETFs), insurance companies, pension funds, and annuities. eMAXX has limited coverage for hedge funds and does not cover banks, government agencies, and households (see, e.g., Becker and Ivashina (2015) and Bretscher et al. (2023)).

[INSERT TABLE 2.3]

We first compute time-series average market shares of implied net sell volume by customer type. Panel A in Table 2.3 shows that bond funds and insurance companies collectively account for more than 90% of the implied sell volume for excluded bonds. Pension funds, annuities, and other customer types account for the small remaining part.

The implied sell volume from eMAXX is measured over an entire quarter, whereas our main analysis focuses on customer sell trades on event days -3 to 0. For insurance companies, we exploit the fact that we can observe their actual trades at the daily level in the NAIC bond transaction data. In each month, we compute the ratio of actual sell volume by insurance companies over event days -3 to 0 from NAIC out of total customer sell volume from TRACE on the same days across all excluded bonds. Panel B in Table 2.3 shows that insurance companies account for 3% of the mean, and 2% of the median customer sell volume for maturity exclusions. For downgrade exclusions, the mean is 9%, and the median is 4%. Insurance companies, therefore, almost exclusively trade away from the exclusion date.

For bond funds, we compute the ratio of implied net sell volume from eMAXX out of total customer sell volume from TRACE aggregated over event days -3 to 0 across all excluded bonds in each month. This ratio would be equal to one if bond funds place all their trades on these event days only and no other customers sell on the same days. Panel B in Table 2.3 shows that this ratio is 0.94 on average and 0.86 in the median month for maturity exclusions. For downgrade exclusions, the ratio is 1.12 on average and 0.54 in the median month. The ratios for the remaining customer types in eMAXX are small because of their small market shares reported in Panel A. Taken together, our findings strongly indicate that bond funds are the dominant sellers of excluded bonds close to the exclusion date.

Next, we analyze the market structure for selling bond funds. We compute the market shares of implied bond fund sell volume by fund family across all excluded bonds in each month. We then rank fund families each month and present time-series average market shares in Panel C in Table 2.3. The fund family with the largest implied sell volume has an average market share of 47% for maturity and 54% for downgrade exclusions. The top 3 fund families account for 72% and 80%, while the top 10 account for nearly the entire implied sell volume. This customer clientele is therefore highly concentrated. We also list the names of fund families with the largest average sell volume across months. These are some of the largest global asset managers and likely have minimal heterogeneity in terms of sophistication or outside options.

Finally, we also determine the number of fund families that sell each excluded bond. Panel D in Table 2.3 shows that the average number of selling fund families is around 5, and the median is 3–4. The small number of sellers per bond also limits potential customer heterogeneity.

2.4.3 Immediacy-providing dealers

We now focus on those dealers that provide immediacy to selling index trackers close to the exclusion date. Panel A in Figure 2.3 and Table 2.4 show how the number of dealers that buy index-excluded bonds from customers on event days -3 to 0 varies over time. The number of immediacy-providing dealers varies more for downgrade exclusions than for maturity exclusions, consistent with downgrades being clustered over time. The average number of dealers is 47 for maturity exclusions and 25 for downgrade exclusions.

It is a small number of dealers that provide immediacy at exclusion compared to the average number of dealers in the corporate bond market of 1,023. These immediacy-providing dealers, however, account for a substantial fraction of customer trading volume in the entire bond market. In an average month, dealers that buy maturity exclusions account for 78% of customer trading volume in the entire bond market. For dealers that buy downgrade exclusions, the average fraction is 48%, and in months with at least five downgrade exclusions, the fraction is 68%. These findings reflect that it is mostly core dealers that provide immediacy for index-excluded bonds, and core dealers also account for most trading activity in the entire bond market. Panel B in Table 2.4 confirms that time-series averages of the cross-sectional distribution of eigenvector centrality scores are substantially higher for index exclusions than for the all corporate bond sample. Panel B also shows that there is substantial variation in centrality across dealers such that we can estimate a meaningful centrality spread.

[INSERT FIGURE 2.3 AND TABLE 2.4]

Next, we investigate the composition of immediacy-providing dealers over time by dividing dealers into two groups. At the end of each month, we rank dealers according to their eigenvector centrality and define the top 5 percentile as core and the rest as peripheral dealers. Panel B in Figure 2.3 shows that core and peripheral dealers are fairly equally represented for maturity exclusions each month, whereas downgrade exclusions feature some spikes typically in months with few exclusions. Panel C in Table 2.4 shows the core dealer share of customer trading volume over time. For index exclusions, core dealers, on average, account for 75% of the dealer buy volume from customers on event days -3 to 0. While core dealers provide most of the immediacy at exclusion, peripheral dealers also account for a meaningful fraction. For comparison, core dealers on average account for 73% of the monthly customer volume in the entire bond market. This similarity in the distribution of customer volume suggests that it is possible to extrapolate from index exclusions to a more general trading scenario.

Finally, we examine the persistence of immediacy-providing dealers. For dealers that buy index-excluded bonds from customers on event days -3 to 0, we compute the probability of buying index-excluded bonds in future exclusion months. Panel D in Table 2.4 reports the probability over various horizons for core and peripheral dealers. For maturity exclusions, the probability that a dealer who provided immediacy this month also provides immediacy next month is 78% for a core dealer and 41% for a peripheral dealer. The probability of providing immediacy within the next 12 months is 97% for core dealers and 75% for peripheral dealers. For downgrade exclusions, it is necessary to consider longer horizon probabilities because downgrade exclusions are clustered over time with zero or few exclusions in some months. The probability of providing immediacy again within the next 12 exclusion months is 91% for core dealers and 54% for peripheral dealers. These findings show that immediacy-providing core dealers are highly persistent over time, whereas some peripheral dealers provide immediacy infrequently.

2.4.4 Trading with core versus peripheral dealers

The decision by index trackers to trade with a given dealer is endogenous. We therefore explore when index trackers trade with core versus peripheral dealers. First, we analyze how the monthly composition of immediacy-providing dealers depends on the demand and supply of immediacy. Specifically, we estimate the following time-series regression separately for maturity and downgrade exclusions:

$$Peripheral\ ratio_m = \beta_0 + \beta_1 Immediacy_m + \epsilon_m \tag{2.1}$$

where $Peripheral\ ratio_m$ is the number of peripheral dealers out of all dealers that buy excluded bonds from customers on event days -3 to 0 in month m. $Immediacy_m$ measures the monthly demand or supply of immediacy. It is reasonable to expect that index trackers demand more immediacy in months during which a large fraction of the index is excluded. We therefore use the percentage of the index excluded to proxy for the demand for immediacy. To measure the supply of immediacy, we use the total volume dealers buy from customers and the total inventory acquired by dealers over event days -3 to 0. Since these variables are highly correlated, we include them in separate regressions. We use robust standard errors and report t-statistics in parenthesis.

[INSERT TABLE 2.5]

Panel A in Table 2.5 shows that the ratio of peripheral dealers increases in months with high demand or supply of immediacy. This finding may suggest that peripheral dealers are more likely to provide immediacy in months when core dealers face inventory constraints. We exploit the variation in core dealer inventories within each month to test this prediction. Specifically, we estimate the following trade-level probit model for peripheral dealer buys ($Peripheral\ buy_{ijt} = 1$) versus core dealer buys ($Peripheral\ buy_{ijt} = 0$) given that a dealer buys from customers on event days -3 to 0:

$$Pr(Peripheral\,buy_{ijt}|Dealer\,buy) = \Phi\left(\beta Core\ inv_t + \eta Inv_{it} + \gamma Log(Trade\ size_{ijt}) + \delta + \epsilon_{ijt}\right) \tag{2.2}$$

where Φ is the cumulative distribution of the standard normal distribution. $Core\ inv_t$ is the inventory buildup aggregated across all core dealers before the current trade and Inv_{it} is the buying dealer's inventory buildup before the current trade. We set the inventory level to \$0 50 trading days before the exclusion date and compute the trade-level cumulative inventory buildup across all excluded bonds (maturity and downgrade exclusions separately) as dealer buys minus the sales. All regressions include either month fixed effects δ_t or bond-times-month fixed effects δ_{jt}. The estimation with month fixed effects requires that both core and peripheral dealers buy excluded bonds in the same month, whereas bond-times-month fixed effects require that both core and peripheral dealers buy the same bond in the same month. We cluster standard errors by bond issuer and month.

Panel B in Table 2.5 shows that peripheral dealers are more likely to provide immediacy when core dealers have higher inventory buildup. We also find that peripheral dealers are less likely to buy excluded bonds when their inventory is higher, and the trade size is larger. The similar coefficient estimates with month versus bond-times-month fixed effects show that these findings are not driven by bond characteristics. Our findings on the decision to trade with core versus peripheral dealers support the Huang and Wei (2017) model.[8] In the Appendix, we show the conditions under which index trackers trade with core versus peripheral dealers in this model. Index trackers sell to peripheral dealers when core dealer inventories are sufficiently high. Since dealers are averse to inventory risk, the propensity to buy decreases with the dealer's inventory level. Finally, peripheral dealers are less likely to execute large customer trades when they unwind inventory by trading with core dealers in the interdealer market.

[8]The models by Üslü (2019) and Colliard et al. (2021) do not distinguish when customers trade with core versus peripheral dealers because customers always trade after matching with a dealer.

2.4.5 Inventory dynamics around index exclusions

We now examine the inventory dynamics of core and peripheral dealers. The inventories are cumulative, aggregated over all dealers according to dealer type, and with a chosen benchmark of \$0 50 trading days before the exclusion date. The daily change in inventory is the total volume of dealer buys minus the sales. We scale the cumulative inventory each month by the total nominal size of bonds excluded in the same month. Figure 2.4 and Table 2.6 present the evolution of average scaled cumulative inventories of index-excluded bonds over the period starting 50 trading days prior to the exclusion date and ending 100 trading days after the exclusion date. Core dealers provide substantially more immediacy than peripheral dealers, and both have a significant inventory buildup leading up to the exclusion date. For maturity exclusions, the inventory buildup starts 3 days before the exclusion date. For downgrade exclusions, the inventory buildup starts earlier partly because dealers also buy bonds on the actual downgrade date, which is typically before the exclusion date.[9] Nonetheless, the inventory buildup is considerably larger, starting 3 days before the exclusion date.

[INSERT FIGURE 2.4 AND TABLE 2.6]

For maturity exclusions, core dealers provide more than four times the immediacy of peripheral dealers when measured on the exclusion date. Both core and peripheral dealers unwind the entire stock of newly acquired inventory over roughly the same time interval. This finding implies that core dealers reduce their inventory about four times faster than peripheral dealers do. For downgrade exclusions, core dealers provide more than three times the amount of immediacy offered by peripheral dealers. The downgraded bonds are riskier and stay longer on dealer balance sheets than maturity-excluded bonds. Even 100 trading days after the exclusion date, dealers are left with a substantial amount of downgraded bonds in inventory. Nevertheless, we again find that core dealers reduce their inventory considerably faster than peripheral dealers do. Over the 100 trading days, core dealers reduce their average scaled inventory by around two-thirds, whereas the reduction is around one-third for peripheral dealers. Our findings reveal that core dealers have a comparative advantage in carrying inventory regarding the speed of inventory adjustment. We test this statement formally in the next section.

2.4.6 Speed of inventory adjustment

Our approach for estimating the speed of inventory adjustment builds on Madhavan and Smidt (1993). For each dealer in each month, we first estimate the inventory adjustment speed using the regression equation:

$$I_t - I_{t-1} = \beta(I_{t-1} - I^*) + \epsilon_t$$

[9] Dick-Nielsen and Rossi (2019) show that the inventory buildup is far less on the downgrade date than on the exclusion date.

where I_t is the cumulative dealer inventory across all excluded bonds on event day t, I^* is the dealer's desired level of inventory, and $\beta \in$ [-1,0] captures the sensitivity of dealer inventory to deviations from the desired inventory level. A more negative value of β corresponds to a higher speed of inventory adjustment. Given the significance of the exclusion event, we estimate the desired level of inventory using the specification:

$$I^* = \alpha_0 + \alpha_1 I_{[t \geq 20]}$$

where α_0 represents the desired level of inventory before the exclusion event $t \in \{-50, \cdots, -20\}$ and α_1 represents the change in desired inventory after exclusion $t \in \{20, \cdots, 100\}$. We do not include the remaining event days around the exclusion date $t = 0$ when estimating the desired inventory level. Finally, we examine the relation between the speed of inventory adjustment and dealer centrality by estimating the regression:

$$\beta_{im} = \alpha + \theta Centrality_{im} + \delta_m + \epsilon_{im} \tag{2.3}$$

where β_{im} is the speed of inventory adjustment for dealer i in month m, $Centrality_{im}$ is the eigenvector centrality score based on all interdealer transactions during the month, and δ_m denotes month fixed effects. We exclude dealers with net negative inventory buildup over event days -3 to 0. Assuming that the excluded bonds are close substitutes, these dealers did not use their inventory to provide immediacy.

[INSERT TABLE 2.7]

Panel A in Table 2.7 reports the regression results for maturity and downgrade exclusions with and without month fixed effects. The coefficient estimates on centrality are negative in all regressions, suggesting that the speed of inventory adjustment increases with centrality. For maturity exclusions, the increase in average inventory adjustment speed from a one standard deviation increase in centrality corresponds to 22% of the mean $(-0.1 * 0.28/-0.13)$ and 48% of the median $(-0.1 * 0.28/-0.06)$. For downgrade exclusions, the increase in average inventory adjustment speed from a one standard deviation increase in centrality corresponds to 15% of the mean $(-0.06 * 0.28/-0.10)$ and 36% of the median $(-0.06 * 0.28/-0.05)$. The coefficient estimates remain negative and statistically significant when we include month fixed effects.

To better understand the economic magnitude of these results, we sort dealers into quartiles according to their eigenvector centrality score and compute the mean and median inventory half-life within each quartile using the formula $-ln(2)/ln(\beta + 1)$. Panel B shows that as we move from the first (peripheral) to the fourth (core) centrality quartile, the average inventory half-life decreases by about 4 trading days for maturity exclusions and about 2.4 trading days for downgrade exclusions. These are economically sizeable differences and show that core dealers unwind their inventory faster than peripheral dealers do.

2.5 The Centrality Spread

In this section, we examine the centrality spread between core and peripheral dealers. We document a customer–dealer centrality discount and an interdealer centrality premium when dealers use their inventories to provide immediacy. Finally, we examine prearranged trades in which the prearranging dealer avoids inventory risk.

2.5.1 Customer–dealer trades

We estimate the centrality spread by comparing transaction prices of the same bond at the same time across dealers when they trade with customers. We study buy and sell transactions separately for maturity exclusions, downgrade exclusions, and for our sample of all corporate bonds. Specifically, we estimate the regression:

$$Price_{ijt} = \beta Centrality_{it} + \gamma Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt} \tag{2.4}$$

where $Price_{ijt}$ is the volume-weighted average dealer buy or sell price measured in basis points for dealer i, bond j, and day t. For index exclusions, we calculate the dealer buy price over event days -3 to 0, where event day 0 is the exclusion date. We compute the dealer sell price on each event day $t \in \{1, ..., 30\}$ after the exclusion date. In our sample of all corporate bonds, the dealer buy and sell prices are computed on each trading day. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. When dealers buy from customers on event days -3 to 0, the centrality scores reflect interdealer trades over the entire month. When dealers sell to customers after the exclusion date, we use centrality scores from the month of exclusion. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. $Volume_{ijt}$ is the cumulative volume of the transactions used to compute the volume-weighted dealer-bond specific price. All regressions include bond-times-day fixed effects δ_{jt} such that we compare prices for the same bond at the same time across dealers. This estimation requires at least two dealer-bond specific observations at the same time. We winsorize prices at the 1st and 99th percentiles and cluster standard errors by bond issuer and trading day. To focus on trades where dealers use their inventory to provide immediacy, we exclude transactions where a dealer buys from a customer and sells the same bond with the same volume to another customer within 60 seconds. For index exclusions, we also exclude dealers with net negative inventory buildup over event days -3 to 0 from the dealer buy price regressions because these dealers did not use their inventories to provide immediacy.[10]

[INSERT TABLE 2.8]

Table 2.8 presents the coefficient estimates of equation (2.4). For maturity exclusions, the coefficient estimate on centrality is positive when dealers buy bonds from customers close to the

[10] We show in the Appendix that our results are robust to including dealers with net negative inventories.

exclusion date. When dealers sell off their newly acquired inventory after the exclusion date, the coefficient estimate on centrality is negative. The fact that dealers with a more central network position buy at higher prices and sell at lower prices on average is synonymous with lower bid-ask spreads and, hence, a centrality discount. A one standard deviation increase in centrality increases the average dealer buy price by 1 bps ($4.090 * 0.24$) and decreases the average dealer sell price by 1.6 bps ($-5.841 * 0.28$). These magnitudes correspond to 6–11% of the average and 15–25% of the median bid-ask spread.[11]

For downgrade exclusions, the coefficient estimate on centrality is positive but statistically insignificant when dealers buy from customers. The lack of statistical significance is partly due to the financial crisis period during which transaction prices are especially volatile for downgraded bonds. When we analyze the centrality spread over time in Table 2.14, we find that the coefficient is 37.89 with a t-statistic of 2.09 in the post-crisis period, where dealers unwind their entire inventory buildup of downgrade exclusions. The coefficient estimate on centrality is negative as dealers unwind their inventory after the exclusion date. A one standard deviation increase in centrality increases the average dealer buy price by 8.3 bps ($32.295 * 0.26$) and decreases the average dealer sell price by 7.1 bps ($-25.562 * 0.28$). These magnitudes correspond to 8–9% of the average and 16–19% of the median bid-ask spread.

Our finding of a centrality discount for index-excluded bonds supports the inventory management channel from Huang and Wei (2017), Üslü (2019), and Colliard et al. (2021). Because dealers use their inventory to provide immediacy to selling index trackers, the price dispersion across dealers reflects compensation for inventory risk. As we would expect, the magnitude of the centrality discount is larger for downgrade exclusions because these bonds are more risky and have longer inventory duration than maturity exclusions. In the Appendix, we illustrate how the customer–dealer centrality discount arises in the Huang and Wei (2017) model. Core dealers derive market power from their network position and can therefore unwind inventory at more favorable prices in the interdealer market. This comparative advantage in managing inventory enables core dealers to offer higher bid prices to index trackers when competing with peripheral dealers to win the customer sell orders.

The last two columns in Table 2.8 show that we also find a centrality discount in the sample of all corporate bonds. A one standard deviation increase in centrality increases the average dealer buy price by 2.9 bps ($10.912 * 0.27$) and decreases the average dealer sell price by 5.1 bps ($-18.588 * 0.27$). These magnitudes correspond to 9–16% of the average and 18–32% of the median bid-ask spread. While the channel is not uniquely identified outside index exclusions, the inventory management channel could potentially be the dominating channel for the average transaction in the corporate bond market. Finally, in all regressions, the coefficient estimate on

[11] The average bid-ask spreads is 15.3 bps, and the median is 6.7 bps for maturity-excluded bonds. For downgrade exclusions, the average bid-ask spread is 87.9 bps, and the median is 44.3 bps. We compute the bid-ask spread for each bond on each event day $t = \{-3, ..., 30\}$ as the difference between the daily volume-weighted average dealer sell and buy price (across all dealers) divided by the mid price.

volume is positive when dealers buy and negative when dealers sell, meaning that transaction costs decrease with the amount of immediacy provided.

2.5.2 Interdealer trades

Dealers can unwind inventory by trading with customers or with other dealers. Schultz (2017) shows that dealers use interdealer trades mostly to manage their inventory risk. We therefore now turn to investigate the centrality spread when dealers trade with each other in the interdealer market. Specifically, we estimate the following regression separately for maturity exclusions, downgrade exclusions, and for our sample of all corporate bonds:

$$Price_{jt} = \beta_1 Buyer\ centrality_t + \beta_2 Seller\ centrality_t + \gamma Log(Volume_{jt}) + \delta_{jt} + \epsilon_{jt} \quad (2.5)$$

where $Price_{jt}$ is the volume-weighted average transaction price measured in basis points between the buying and selling dealer for bond j on day t. For index exclusions, we compute the interdealer price on each event day $t \in \{-3, ..., 30\}$ where event day 0 is the exclusion date. In our sample of all corporate bonds, the interdealer prices are computed on each trading day. $Buyer\ centrality_t$ and $Seller\ centrality_t$ denote the eigenvector centrality scores of the buying and selling dealer based on all interdealer transactions during the exclusion month. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. $Volume_{jt}$ is the cumulative volume of the transactions used to compute the interdealer price. All regressions include bond-times-day fixed effects δ_{jt} such that we compare prices for the same bond at the same time across dealer pairs. We winsorize prices at the 1st and 99th percentiles and cluster standard errors by bond issuer and trading day.

[INSERT TABLE 2.9]

Table 2.9 shows negative coefficients on buyer centrality and positive coefficients on seller centrality in all regressions. The fact that dealers with more central network positions buy at lower prices and sell at higher prices on average is synonymous with core dealers charging higher bid-ask spreads. Our finding of a centrality premium in the interdealer market is consistent with Di Maggio et al. (2017), who document an interdealer centrality premium across all corporate bonds. By using information-free trades around index exclusions, we can rule out that the interdealer centrality spread reflects adverse selection for these trades. Since dealers use their inventories to provide immediacy for index-excluded bonds, the interdealer centrality spread reflects compensation for inventory risk and interdealer frictions. On the one hand, core dealers' comparative advantage in carrying inventory allows them to charge lower transaction costs to peripheral dealers. On the other hand, core dealers derive market power from their comparative advantage and may therefore charge higher transaction costs to peripheral dealers. Our finding of an interdealer centrality premium suggests that market power dominates in interdealer trades consistent with the inventory management channel. In the Appendix, we illustrate how dealer market power results in an interdealer centrality premium in the Huang and Wei (2017) model.

2.5.3 Prearranged trades

The inventory management channel affects the centrality spread for those trades only where dealers use their inventories. When a seller contacts a dealer, the dealer may offer immediate execution and take the bonds into inventory (usually called a principal trade) or ask the seller to wait until a matching counterparty can be found (prearranged trade). In the latter case, the dealer assumes no inventory risk and acts as a broker between the seller and buyer. We therefore use prearranged trades as a proxy for aversion to inventory risk and to analyze the centrality spread for a set of trades unaffected by the inventory management channel.

We define a prearranged trade as one in which the same dealer buys and sells the same bond with the same volume within 60 seconds (similar to, e.g., Bessembinder et al. (2018) and Schultz (2017)). We consider trade sizes of at least $100,000 only. For index exclusions, we identify prearranged trades on event days -3 to 0 in each month. In the sample of all corporate bonds, we identify prearranged trades on all trading days. We divide prearranged trades into four groups based on counterparty type: (1) the dealer buys from a customer and sells to a customer (CDC), (2) the dealer buys from a dealer and sells to a dealer (DDD), (3) the dealer buys from a customer and sells to a dealer (CDD), and (4) the dealer buys from a dealer and sells to a customer (DDC).

[INSERT TABLE 2.10]

First, we follow Friewald and Nagler (2019) and use the fraction of prearranged trades as a proxy for aversion to inventory risk. For index-excluded bonds, we compute the average ratio of prearranged customer volume to the total customer volume using transactions on event days -3 to 0 in each month. We then compute the average ratio across months. For comparison, we also compute the average monthly fraction of prearranged volume for our sample of all corporate bonds using transactions during the entire month. Panel A in Table 2.10 shows that peripheral dealers use substantially more prearranged trades than core dealers do. For maturity exclusions, peripheral dealers, on average, prearrange 11.04% of their trading volume compared to 4.72% for core dealers. For downgrade exclusions, the fractions are 17.16% for peripheral dealers and 9.61% for core dealers. The last column shows that in the sample of all corporate bonds, the ratio for peripheral dealers is more than twice that of core dealers. These findings suggest that peripheral dealers are more averse to inventory risk than core dealers.[12] Core dealers are therefore more willing to use their inventory to provide immediacy consistent with the inventory management channel.

Next, we compute the markup from the prearranging dealer's point of view as the sell price minus the buy price divided by the mid-price and winsorize markups at the 1st and 99th percentiles. Panel B in Table 2.10 shows that downgrade exclusions have the highest average markups, followed by the sample of all corporate bonds and maturity exclusions. The

[12] Li and Schürhoff (2019) also find that peripheral dealers use more prearranged trades than core dealers in the municipal bonds market.

average trade size is typically larger for index exclusions than for the all corporate bond sample, reflecting that trades around exclusions are those of large institutional index trackers. Across all three samples, average centrality scores are fairly similar for each type of prearranged trade. We report the average centrality score for each dealer in the prearranged trade. For DDD prearranged trades, the selling dealer has a higher centrality score than the buying dealer on average. For CDD prearranged trades, the prearranging dealer has a lower centrality score than the buying dealer on average. We find that the prearranging dealer sells the bond to a dealer with a higher centrality score in 78–79% of the cases. For DDC prearranged trades, the selling dealer has a higher centrality score than the prearranging dealer. In 75–76% of the cases, the prearranging dealer buys the bond from a dealer with a higher centrality score. These findings also suggest that peripheral dealers are more averse to inventory risk. When a customer wants to buy or sell, a peripheral dealer avoids inventory risk by prearranging the trade with a core dealer.

Finally, we exploit that predictions of the centrality spread for prearranged trades differ across economic channels. We therefore estimate the following regression separately for maturity exclusions, downgrade exclusions, and for our sample of all corporate bonds:

$$Markup_{ijt} = \beta Centrality_{it} + \gamma Log(Trade\ size_{ijt}) + \delta_{jt} + \epsilon_{ijt} \tag{2.6}$$

where $Markup_{ijt}$ is measured in basis points for the prearranging dealer i for bond j on day t. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. We include the centrality score for each dealer in the prearranged trade. All regressions include bond-times-day fixed effects δ_{jt} such that we compare markups for the same bond at the same time across dealers. We cluster standard errors by issuer and month for index exclusions and by issuer and trading day in the all corporate bond sample.

[INSERT TABLE 2.11]

Table 2.11 shows that the coefficient estimates on centrality are statistically insignificant from zero for CDC prearranged trades. Since the dealer assumes no inventory risk in these trades, the inventory management channel predicts that the centrality spread should be zero. Importantly, the centrality spread for CDC trades cannot reflect any frictions from the interdealer market because each trade involves a single dealer only. In other types of prearranged trades, the prearranging dealer buys from and/or sells to another dealer. When the customer demands liquidity in CDD and DDC trades, the prearranging dealer, in turn, demands liquidity from another dealer. Since core dealers trade on better terms in the interdealer market, they can offer lower markups to their customers. The inventory management channel therefore predicts a centrality discount for CDD and DDC trades consistent with the negative coefficient estimates on prearranging dealer centrality in Table 2.11. We also find that the markup typically increases when the end buyer or end seller has a more central network position. This finding also supports the inventory management channel because end dealers with central network positions charge higher transaction costs to the prearranging dealer. We find the same effect of end dealer network position in DDD trades. Interestingly, the negative coefficient estimates on prearranging dealer centrality imply a centrality discount for DDD trades. Core dealers therefore do not have market power when they prearrange trades between dealers only.

Adverse selection and search-based models with customer clienteles have different predictions of the centrality spread for prearranged trades. The prearranging dealer does not take ownership of the bond and is, therefore, not concerned about the risk of trading with potentially informed counterparties. The centrality discount for CDD, DDC, and DDD trades therefore cannot reflect adverse selection. Search-based models with customer clienteles predict either a centrality premium or discount when customers are heterogeneous, while the centrality spread is zero when customers are homogeneous. Reconciling this framework with our findings requires that customers are homogeneous in CDC trades while customers are heterogeneous in CDD and DDC trades. For index exclusions, index trackers are clearly demanding liquidity in CDD trades. The centrality discount for these trades is therefore unlikely to reflect customer clientele differences across dealers. We return to these alternative explanations of the centrality spread in Section 2.7. Finally, the coefficient estimate on trade size is mostly negative, consistent with findings by, e.g., Schultz (2001), Chakravarty and Sarkar (2003), Edwards et al. (2007), and Feldhütter (2012).

2.6 Dealer behavior and centrality spread over time

Recent papers find that liquidity provision in the corporate bond market changed after the 2007–2009 financial crisis. Dealers reduced the use of inventories for market making (Bao et al. (2018), Bessembinder et al. (2018), and Schultz (2017)) and increased the cost of immediacy (Bao et al. (2018), Dick-Nielsen and Rossi (2019), and Choi et al. (2022)). These findings are consistent with an increase in inventory holding costs due to post-crisis regulatory reforms. In this section, we use the time-series variation in inventory holding costs to analyze dealer behavior and the centrality spread over time.

2.6.1 Inventory dynamics by subperiod

Dick-Nielsen and Rossi (2019) show that dealers unwind inventories of maturity and downgrade exclusions faster after the financial crisis. This change in dealer behavior is consistent with post-crisis regulations discouraging dealers from holding risky inventories. Their sample ends in November 2013 before new regulations, specifically the Volcker Rule, are fully implemented.[13]

[13]Post-crisis regulations include the Volcker Rule which is part of the Dodd-Frank Act signed into law on July 21, 2010. The Volcker Rule prohibits banks (and hence bank-affiliated dealers) from engaging in proprietary trading but includes a provision that permits market making. In practice, however, it is challenging to distinguish between

We therefore use our longer sample period to study dealer behavior after the implementation date by dividing our sample into four subperiods. The pre-crisis period is from July 2002 to June 2007, the crisis period is from July 2007 to December 2009, the post-crisis period is from January 2010 to June 2014, and the Volcker period is from July 2014 to August 2018.[14]

[INSERT FIGURE 2.5 AND TABLE 2.12]

Figure 2.5 and Table 2.12 show the average scaled cumulative inventories for maturity and downgrade exclusions by subperiod. Before the crisis, dealers have 25% of the inventory buildup for maturity exclusions left after 30 days compared to 1% in the post-crisis period. For downgrade exclusions, the numbers are 79% before the crisis and 27% in the post-crisis period. Dick-Nielsen and Rossi (2019) attribute this change in dealer behavior to an anticipation effect of new regulations. In January 2011, the Financial Stability Oversight Council made recommendations on implementing the Volcker Rule, including how to distinguish allowed market marking from prohibited proprietary trading. Market making is likely to have rapid inventory turnover with most profits from bid-ask spreads, whereas proprietary trading has modest inventory turnover with most profits from price appreciation. The faster unwinding of inventories in the post-crisis period is therefore consistent with this interpretation of market making.

The final regulations of the Volcker Rule were approved on December 10, 2013 following several years of legal drafting. The final rule stipulates that positions held for less than 60 days are presumed to be proprietary trading unless the banking entity can demonstrate that they are for market making purposes.[15] Figure 2.5 and Table 2.12 show that after the implementation of the Volcker Rule, dealers keep 22% of the inventory buildup of maturity exclusions and 79% of the inventory buildup for downgrade exclusions even 100 trading days after exclusion. This finding suggests that dealers keep excluded bonds on inventory for more than 60 days with a view to avoid the proprietary trading classification. Because maturity exclusions are money market instruments (i.e., investment grade bonds with maturities less than one year), dealers may sell off some of these bonds relatively quickly to money market funds and demonstrate that these positions are for market making. Downgrade exclusions are riskier securities without a sizeable natural buyer clienteles (e.g., high-yield funds). Dealers may therefore find it more

market making and proprietary trading. The Volcker Rule was originally scheduled to take effect on July 21, 2012 but the actual implementation date was postponed until April 1, 2014. Large banks were required to start reporting quantitative measurements from July 2014 and must be fully compliant with the regulation by July 21, 2015.

[14] Dick-Nielsen and Rossi (2019) show in Table 15 that bank-affiliated dealers provide most of the immediacy for index exclusions. For this reason, we use July 2014 as the starting date of the Volcker period because large banks have to report quantitative measures from this month. We obtain qualitatively similar results when we use April 2014 or July 2015 as the starting date.

[15] The amendments to the Volcker Rule published on August 20, 2019 eliminates this 60-day presumption and instead includes a new presumption that positions held for more than 60 days are not considered proprietary trading. This amendment is effective from January 1, 2020.

difficult to convince the regulator that short-term positions in these bonds are for market making purposes. Taken together, our results show that the anticipation effect differs from the actual implementation of new regulations.

2.6.2 Network centrality by subperiod

Core dealers' connection advantage in the interdealer network becomes more valuable when inventory costs are high. An increase in inventory holding costs therefore increases the comparative advantage of core dealers in managing inventory. Core dealers should therefore account for more trading activity in periods with high inventory costs. To test this prediction, we weigh eigenvector centrality scores by dealer buy volume from customers each month. This measure reflects the extent to which central dealers intermediate customer buy volume. We then estimate the following time-series regression separately for maturity exclusions, downgrade exclusions, and for our sample of all corporate bonds:

$$VW\ centrality_m = \beta_0 + \beta_1 Crisis_m + \beta_2 Post\text{-}crisis_m + \beta_3 Volcker_m + \epsilon_{im} \tag{2.7}$$

where $VW\ centrality_m$ is the volume-weighted average eigenvector centrality score in month m. We compute the centrality score for each dealer based on all interdealer transactions during the exclusion month. For index exclusions, we weigh centrality scores by the buy volume from customers over event days [-3, 0] where event day 0 is the exclusion date. In the sample of all corporate bonds, we weigh centrality scores by the buy volume from customers over the entire month. We use the pre-crisis period as the omitted group and include indicator variables for the remaining subperiods. We use robust standard errors and report t-statistics in parenthesis.

[INSERT TABLE 2.13]

Panel A in Table 2.13 shows positive and statistically significant coefficient estimates in the post-crisis and Volcker periods. Core dealers therefore account for a greater share of customer buy volume after the financial crisis, where regulatory reforms increased the cost of holding inventory. Higher inventory holding costs also increase the incentive for dealers to become better connected in the network with a view to mitigate their inventory risk. We therefore analyze within-dealer variation in centrality by estimating the following panel regression:

$$Centrality_{im} = \beta_0 + \beta_1 Crisis_m + \beta_2 Post\text{-}crisis_m + \beta_3 Volcker_m + \delta_i + \epsilon_{im} \tag{2.8}$$

where $Centrality_{im}$ is the eigenvector centrality score for dealer i in month m. We use the pre-crisis period as the omitted group and include indicator variables for the remaining time periods together with dealer fixed effects δ_i. For index exclusions, we consider dealers that buy from customers on event days -3 to 0 only. Standard errors are clustered by dealer and month with t-statistics in parenthesis.

Panel B in Table 2.13 shows that dealers increase their network centrality in the post-crisis and Volcker periods. The interdealer network has therefore become more dense after the financial crisis, consistent with an increase in inventory holding costs. Taken together, the changes in dealer behavior over time support the inventory management channel with time-varying inventory holding costs.

2.6.3 Centrality spread by subperiod

The inventory management channel has an ambiguous prediction on the time-series variation in the centrality spread. On the one hand, higher inventory costs increase the comparative advantage of core dealers in managing inventory. This feature predicts a more pronounced centrality spread, i.e., a more negative centrality discount for customer–dealer trades and a more positive centrality premium for interdealer trades. On the other hand, higher inventory costs increase the incentive for dealers to become better connected in the interdealer network. A more dense interdealer network reduces the connection asymmetry between core and peripheral dealers and, therefore, predicts a less pronounced centrality spread.

[INSERT TABLE 2.14]

We analyze the time-series variation in the centrality spread by interacting the centrality measure(s) in regression equations (2.4) and (2.5) with indicator variables for each subperiod. Panel A and B in Table 2.14 show that the centrality discount for customer–dealer trades and the centrality premium for interdealer trades remain statistically significant in most subperiods. The insignificant centrality spread for downgrade exclusions during the crisis likely reflects that transaction prices are especially volatile for downgraded bonds in this period.

Table 2.14 also shows that the magnitude of the centrality spread is typically smaller after the crisis than before the crisis. In the last row of each panel, we test if the change in the centrality spread is statistically significant. We find that the interdealer centrality premium decreases significantly in the post-crisis and Volcker periods for downgrade exclusions and the all corporate bond sample, while the decrease is insignificant for maturity exclusions. These findings suggest that higher inventory costs after the crisis predominantly affect the centrality spread through the increased network density. Consistent with this interpretation, we also find that the customer–dealer centrality discount is significantly less pronounced in the Volcker period and, in some cases, in the post-crisis period.

2.7 Alternative explanations

Using trades around index exclusions isolate the inventory management channel and rule out confounding alternative explanations of the centrality spread. In addition, the inclusion of bond-times-day fixed effects in our regressions absorb potential variation that otherwise may be linked to several other channels. We now show that proxies motivated by alternative explanations cannot explain the centrality spread for index exclusions.

[INSERT TABLE 2.15 AND 2.16]

2.7.1 Adverse selection

Babus and Kondor (2018) develop a network model in which market participants have private information. The model shows that core dealers are less exposed to adverse selection because they observe more order flow. This feature allows core dealers to charge lower spreads than peripheral dealers, resulting in a centrality discount. Adverse selection is unlikely to explain our centrality spread because mechanical index rules, not information, dictate the decision to trade by index trackers. While maturity exclusions are entirely information-free, Dick-Nielsen and Rossi (2019) note that if prices incorporate information slowly then the cost of immediacy for downgrade exclusions could potentially reflect new information released on the downgrade date (i.e., before the exclusion date). The inclusion of bond-times-day fixed effects in our regressions absorbs all time-varying bond and issuer-specific information, but dealers may still have different capacities to obtain new information. We therefore use transactions on event days -3 to 0 to compute the dealer-level fraction of total order flow across all excluded bonds in each month. The fraction of total order flow proxies for the dealer's ability to learn from the order flow.

Table 2.15 shows that the coefficient estimates on centrality for customer–dealer trades remain unchanged when we include this proxy for adverse selection. For maturity exclusions, dealers that observe more order flow buy at lower prices on average (implying a higher bid-ask spread) in contrast to the prediction from adverse selection models. For downgrade exclusions where asymmetric information is potentially a concern, the coefficient estimates on order flow are statistically insignificant. Table 2.16 presents the results for interdealer trades. While the coefficient estimates on order flow have the predicted sign from adverse selection models, the coefficient estimates on centrality remain unchanged. Adverse selection, therefore, cannot explain our results.

2.7.2 Customer clienteles

Search-based models with customer clienteles feature heterogeneous customers segmented on the need for execution speed. Customers choose to trade with dealers based on trade execution speeds and transaction costs. Our finding that index trackers trade mostly with core dealers supports search-based models with customer clienteles in which core dealers have fast execution speed. In this section, however, we argue that these models cannot explain the centrality spread for index exclusions.

Execution speed

In Li and Schürhoff (2019), customers face a trade-off between execution speed and cost. Core dealers offer faster execution and charge higher transaction costs to fast-preference customers. This centrality premium arises when customers have weak outside options, need fast execution speed, and dealers have sufficiently high bargaining power. In contrast, we document a centrality discount for index-excluded bonds where index trackers have weak outside options, need fast execution speed, and dealers have essentially all bargaining power. Index trackers do not trade off execution speed against cost because they require immediacy at exclusion.

Outside options

In Hollifield et al. (2017), fast-preference customers have stronger outside options, unlike Li and Schürhoff (2019). Their model predicts a centrality discount when core and peripheral dealers serve sufficiently different customer clienteles. Core dealers offer fast execution speed and attract customers with stronger outside options that negotiate lower transaction costs. Index trackers need fast execution but have weak outside options when they sell bonds exiting the index. The need for execution speed implies that dealers possess essentially all bargaining power vis-á-vis index trackers when negotiating the price. The customer–dealer centrality discount for index exclusions is therefore unlikely to reflect matching between core dealers and fast-preference customers with strong outside options.

We use trade sizes to investigate if core dealers trade more frequently with index trackers having stronger outside options. Large trades are typically associated with customers that have stronger bargaining positions (see, e.g., Green et al. (2007), Feldhütter (2012), and Friewald and Nagler (2019)). For each dealer in each month, we compute the number of block trades (defined as trade sizes of at least 5 million USD) out of all dealer buys from customers on days -3 to 0 across excluded bonds. Table 2.15 shows that dealers with a higher ratio of block trades typically charge lower average transaction costs to their customers consistent with stronger customer bargaining positions. The coefficient estimate on block trades, however, is statistically insignificant for maturity exclusions when dealers buy and marginally significant for downgrade exclusions. Importantly, we find that the coefficient estimates on centrality remain unchanged when we include this proxy for customer bargaining position. The customer–dealer centrality discount is therefore not explained by matching between core dealers and customers with strong outside options. Hollifield et al. (2017) do not model the interdealer market, but for completeness, we show in Table 2.16 that the coefficient estimates on centrality for interdealer trades remain unchanged when we include the proxy for customer bargaining position.

Next, we analyze the relationship between trade size and centrality. If core dealers, on average, trade more with customers who have stronger bargaining positions, then we should expect a positive relationship. We therefore estimate the regression:

$$Log(Trade\ size_{ijt}) = \sum_s \beta_s Centrality_{it} \mathbb{1}_s + \delta_{jt} + \epsilon_{ijt} \tag{2.9}$$

where $Trade\ size_{ijt}$ is for dealer i, bond j, and day t. For index exclusions, we use transactions where dealers buy from customers on event days -3 to 0 and transactions where dealers sell to customers on event days $t \in \{1, ..., 30\}$. In our sample of all corporate bonds, we use customer–dealer trades on all trading days. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. $\mathbb{1}_s$ is an indicator variable that takes a value of one in time period s. All regressions include bond-times-day fixed effects δ_{jt} and we cluster standard errors by bond issuer and trading day. We consider trade sizes of at least $100,000 to focus on institutional-sized transactions.

[INSERT TABLE 2.17]

Table 2.17 shows negative coefficient estimates on centrality in the pre-crisis period for maturity exclusions and the all corporate bond sample. Core dealers therefore, on average, trade in smaller sizes for institutional-sized transactions in contrast to the prediction from search-based models with customer clienteles. During the crisis period, the relationship between trade size and centrality is mostly insignificant. These findings suggest that the customer–dealer centrality discount in the pre-crisis and crisis periods from Table 2.14 is not driven by matching between core dealers and customers with strong outside options.

Dealer specialization

Sambalaibat (2022) shows that a core-periphery network structure arises when ex-ante identical dealers specialize in heterogeneous customer clienteles. Core dealers specialize in fast-preference customers with frequent trading needs (e.g., index trackers), whereas peripheral dealers specialize in slow-preference customers with infrequent trading needs (e.g., pension funds). Since customers of core dealers trade more frequently, core dealers receive a larger customer order flow and trade more in the interdealer market, translating into a central network position. Core dealers attract fast-preference customers by offering fast execution speed and by charging lower transaction costs, resulting in a customer–dealer centrality discount. This difference in clientele across dealers is unlikely to explain the centrality spread that we estimate within a specific customer clientele (index trackers).

We use dealer market shares of index-excluded bonds to proxy for dealer specialization. Index trackers are a specific clientele that need fast execution speed and have frequent trading needs. Dealers that specialize in index trackers will likely attract other fast-preference customers with frequent trading needs (e.g., money market funds). For each dealer in each month, we compute the share of total dealer buy volume from customers across excluded bonds on event days -3 to 0. Table 2.15 shows that the coefficient estimates on centrality for customer–dealer trades remain unchanged when we include this proxy for dealer specialization. For maturity exclusions, dealers with a higher market share buy at lower average prices (implying a higher bid-ask spread) in contrast to the prediction from dealer specialization. For downgrade exclusions, the coefficient estimates on market share are statistically insignificant. Sambalaibat (2022) also shows that dealer specialization generate an interdealer centrality premium. Core dealers provide liquidity to peripheral dealers and charge higher transaction costs for doing so. Table 2.16 shows that the coefficient estimates on centrality for interdealer trades remain unchanged when we include the proxy for dealer specialization. When controlling for dealer centrality, the coefficient estimates on market share have the opposite sign to the prediction from dealer specialization. Taken together, dealer specialization is unlikely to explain the centrality spread for index exclusions.

Proxies based on institutional bond holdings

In this section, we use quarterly institutional bond holdings from eMAXX to measure customer heterogeneity when dealers buy from customers on event days -3 to 0. For each bond exclusion, we identify customers that are net sellers from 3 months before to 2 months after the exclusion date and construct two variables. First, we count the number of selling customers per bond. Second, we compute the standard deviation of customer size across the selling customers for each bond. We measure the size of each customer by aggregating the par value of the customer's entire fixed income holdings in eMAXX on the most recent reporting date in the 3 months before the exclusion month. We expect bonds with a larger number of sellers and more dispersion in seller size to have larger customer heterogeneity. We then estimate the regression:

$$Buy\ price_{ijt} = \beta_1 Centrality_{it} * High_{jt} + \beta_2 Centrality_{it} + \gamma Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt} \quad (2.10)$$

where $Buy\ price_{ijt}$ is the volume-weighted average dealer buy price from customers over event days -3 to 0 for dealer i, bond j, and time t. $High_{jt}$ is an indicator variable that takes a value of 1 when bond j has above median customer heterogeneity at time t. The remaining variables are the same as in equation (2.4).

[INSERT TABLE 2.18]

Panel A in Table 2.18 shows that the coefficient estimate on the interaction variable is statistically insignificant for both maturity and downgrade exclusions. The centrality discount is therefore not more pronounced for bonds with higher customer heterogeneity. This finding supports the interpretation that index trackers have minimal heterogeneity in terms of sophistication or outside options. We also show that the results are similar when we measure customer heterogeneity for bond funds only and when we include all customer types in eMAXX.

Next, we limit potential customer heterogeneity across different customer clienteles by filtering out customer sell trades on event days -3 to 0 that could involve customers other than bond funds. First, we exclude trades potentially from insurance companies by using the NAIC data. For each bond exclusion, we remove all customer sell trades from TRACE on event days -3 to 0 with trade sizes up to the largest actual sell trade by insurance companies from NAIC on the same day. Second, we remove all customer sell trades from TRACE with trade sizes up to the largest implied net sell volume from customers in eMAXX that are neither bond funds nor insurance companies. We then use this filtered sample to estimate the regression from equation (2.4) for different subsamples based on the number of selling fund families N.

Panel B in Table 2.18 shows that the coefficient estimate on centrality remains positive (i.e., a centrality discount) when dealers buy from customers close to the exclusion date. The sample requirement $N \geq 1$ means that a bond must have at least one fund family with the implied net sell volume above zero in that bond. The sample sizes and results are almost identical when we drop this requirement ($N \geq 0$). These results suggest that the variation in customer clienteles is unlikely to explain the centrality spread for index exclusions. In our most restrictive specification ($N = 1$), we estimate the centrality spread for excluded bonds where strictly one fund family has implied net sell volume greater than zero in that bond, while all other fund families have implied net sell volume equal to zero. For maturity exclusions, we find a more pronounced centrality discount that remains statistically significant. For downgrade exclusions, the coefficient estimate on centrality is positive but not statistically significant. These results suggest that variation within the customer clientele of bond funds is unlikely to explain the centrality spread.

Finally, we use the timing of sales to differentiate index trackers from customers who do not track the index. Index trackers should sell near the exclusion date, whereas other customers should either sell further away or avoid selling altogether. We therefore estimate the regression from equation (2.4) for event windows with different lengths using our main sample. Panel C in Table 2.18 shows that the coefficient estimates on centrality remain almost the same for the different event windows.

2.8 Conclusion

In this paper, we examine how dealer network position affects the cost of immediacy. We document a centrality discount for customer–dealer trades and a centrality premium for interdealer trades consistent with recent OTC network models of inventory risk. In these models, dealers use the interdealer network to unwind inventory. Core dealers' comparative advantage in managing inventory entails that customer transaction costs decrease with centrality, whereas interdealer transaction costs increase with centrality. We use trades around index exclusions to isolate the inventory management channel and avoid confounding effects from adverse selection and heterogeneous customer clienteles.

Consistent with the inventory management channel, we show that core dealers have a comparative advantage in carrying inventory. Core dealers provide more immediacy, unwind their newly acquired inventory faster, and use fewer prearranged trades than peripheral dealers do. When dealers prearrange trades between selling and buying customers, we find an insignificant centrality spread consistent with dealers taking zero inventory risk. Finally, we show that after the financial crisis, core dealers account for more trading activity, and dealers increase their network connections, which is consistent with post-crisis regulatory reforms increasing the cost of holding inventory.

Our results using trades from the entire corporate bond market remain qualitatively similar to the results for index exclusions. The inventory management channel is, therefore, potentially the dominating channel for the average transaction in the corporate bond market. Because the use of inventories for market-making is a fundamental feature of OTC markets, our findings are also important for understanding the centrality spread in other markets.

2.9 Tables and Figures

Table 2.1: Summary statistics

This table presents summary statistics for our sample of monthly exclusions from the Bloomberg Barclays US Corporate Bond Index over the period July 2002 to August 2018. We focus on two exclusion reasons. The bond's maturity can become less than 1 year during the month. The bond can be downgraded from investment grade to speculative grade during the month. In both cases, the bond is excluded at the end of the month. Panel A shows the number of excluded bonds with transactions in TRACE, the number of bonds bought (sold) by dealers (customers) at exclusion (event days -3 to 0 where event day 0 is the exclusion date), and the number of bonds sold (bought) by dealers (customers) after exclusion (event days 1 to 30). Panel B reports the number of unique bonds together with average bond characteristics. Coupon is measured in percent, issue size is in millions of USD, and initial maturity is measured in years. We also show summary statistics for our sample of all corporate bonds which are non-convertible corporate bonds that are not rule 144A.

Panel A: Index exclusions

	Number of exclusions	Exclusions in TRACE	Dealer buys at exclusion	Dealer sells after exclusion
Maturity exclusions	5,389	5,314	5,185	5,263
Downgrade exclusions	1,377	1,295	1,265	1,294

Panel B: Bond characteristics

	Bonds	Coupon	Issue size	Initial maturity
Maturity exclusions	5,389	5.69	706.33	6.70
Downgrade exclusions	1,310	6.80	626.08	14.46
All corporate bonds	67,108	3.80	257.67	7.90

Table 2.2: Trading activity around index exclusions

This table shows the average daily trading volume for customer–dealer and interdealer trades scaled by the total nominal size of bonds excluded at the event. The average scaled volume is measured in percent, event day 0 is the exclusion date, and event time is measured in trading days. We aggregate trading volume across all bonds excluded in a given month and scale by the total nominal size of bonds excluded in the same month. Finally, we compute the average scaled trading volume across all months.

	Customer–dealer				**Interdealer**			
	Maturity		Downgrade		Maturity		Downgrade	
Event day	Volume	Fraction	Volume	Fraction	Volume	Fraction	Volume	Fraction
-100	0.20	0.15	0.47	0.16	0.08	0.36	0.24	0.44
-50	0.23	0.17	0.57	0.19	0.09	0.40	0.28	0.51
-40	0.21	0.15	0.43	0.15	0.08	0.35	0.27	0.49
-30	0.25	0.18	0.46	0.15	0.12	0.51	0.19	0.34
-20	0.30	0.22	0.55	0.19	0.08	0.35	0.23	0.42
-10	0.30	0.22	0.93	0.32	0.13	0.56	0.32	0.59
-9	0.33	0.24	0.96	0.32	0.11	0.46	0.33	0.59
-8	0.40	0.29	1.14	0.38	0.12	0.54	0.41	0.74
-7	0.35	0.26	1.20	0.41	0.12	0.52	0.41	0.74
-6	0.36	0.26	1.00	0.34	0.11	0.46	0.38	0.68
-5	0.37	0.28	0.89	0.30	0.14	0.59	0.30	0.54
-4	0.48	0.35	1.00	0.34	0.12	0.51	0.43	0.78
-3	1.07	0.79	1.30	0.44	0.19	0.81	0.41	0.75
-2	1.55	1.15	1.40	0.47	0.26	1.13	0.36	0.64
-1	0.86	0.63	1.76	0.60	0.22	0.93	0.45	0.80
0	1.36	1.00	2.96	1.00	0.23	1.00	0.55	1.00
1	0.60	0.44	1.24	0.42	0.20	0.88	0.47	0.85
2	0.55	0.41	1.26	0.42	0.20	0.88	0.48	0.87
3	0.48	0.36	1.09	0.37	0.18	0.77	0.49	0.88
4	0.44	0.32	0.96	0.33	0.15	0.67	0.35	0.62
5	0.41	0.30	1.00	0.34	0.15	0.67	0.29	0.53
6	0.39	0.29	0.72	0.24	0.15	0.64	0.32	0.57
7	0.36	0.26	0.83	0.28	0.14	0.60	0.34	0.61
8	0.36	0.27	0.77	0.26	0.15	0.63	0.37	0.68
9	0.37	0.27	0.64	0.22	0.15	0.65	0.24	0.44
10	0.33	0.24	0.83	0.28	0.14	0.60	0.27	0.49
20	0.25	0.19	0.55	0.19	0.08	0.33	0.21	0.37
30	0.24	0.18	0.50	0.17	0.09	0.41	0.22	0.39
40	0.24	0.17	0.68	0.23	0.07	0.29	0.22	0.39
50	0.27	0.20	0.51	0.17	0.08	0.36	0.27	0.48
100	0.24	0.18	0.72	0.25	0.07	0.28	0.28	0.51

Table 2.3: Index tracker characteristics

This table presents characteristics for customers that sell excluded bonds around the exclusion date. We use quarterly observations of institutional bond holdings from Refinitiv eMAXX to identify customers that sell excluded bonds from the 3 months before to the 2 months after the exclusion date. Panel A shows the time-series average market shares of implied sell volume by customer type. Panel B reports the ratio of customer-type sell volume out of total customer sell volume aggregated over event days -3 to 0 across all excluded bonds in each month. We use the implied sell volume from eMAXX for bond funds and the actual sell volume from NAIC bond transactions data for insurance companies. Panel C presents the time-series average market share of monthly bond fund sell volume for excluded bonds. We rank fund families each month by their sell volume and list those with the largest average sell volume across months. Panel D reports the number of selling fund families per bond exclusion. The sample period is from July 2002 to August 2018.

Panel A: Market shares of implied sell volume

	Bond funds	Insurance	Pension	Annuities	Other
Maturity exclusions	0.58	0.32	0.05	0.04	0.02
Downgrade exclusions	0.43	0.48	0.05	0.04	0.00

Panel B: Sell volume out of total customer sell volume at exclusion

	Mean	SD	P10	P50	P90
Maturity exclusions:					
Bond funds	0.94	0.77	0.30	0.86	1.54
Insurance (actual trades)	0.03	0.05	0.00	0.02	0.07
Downgrade exclusions:					
Bond funds	1.12	1.88	0.07	0.54	2.32
Insurance (actual trades)	0.09	0.16	0.00	0.04	0.29

Panel C: Market share of implied bond fund sell volume by fund family

	Top 1	Top 2	Top 3	Top 5	Top 10
Maturity exclusions	0.47	0.64	0.72	0.81	0.91
Downgrade exclusions	0.54	0.71	0.80	0.89	0.96

Rank	Name	Rank	Name	Rank	Name
1	Vanguard Group	4	PIMCO	7	Wellington Management
2	Blackrock	5	Dimensional Fund Advisors	8	Capital Group
3	State Street Corporation	6	Fidelity Investments	9	JPM Asset Management

Panel D: Number of fund families per bond exclusion

	Mean	SD	P10	P50	P90
Maturity exclusions	4.87	4.05	1	4	10
Downgrade exclusions	4.97	5.29	0	3	12

Table 2.4: Dealer characteristics

This table presents dealer characteristics for index exclusions and the entire corporate bond market. Panel A shows the number of dealers per month that buy excluded bonds from customers at exclusion (event days -3 to 0) and the number of dealers per month in the entire corporate bond market. Panel B presents time-series averages of the cross-sectional distribution of eigenvector centrality scores. At the end of each month, we use interdealer transactions from our sample of all corporate bonds to computer dealer-level eigenvector centrality scores. We then show the average distribution across months for those dealers that buy excluded bonds from customers at exclusion (event days -3 to 0) and also for all dealers featured in our sample of all corporate bonds. Panel C reports the core dealer share of monthly customer volume. For index exclusions, we consider trades where dealers buy from customers on event days -3 to 0. In the sample of all corporate bonds, we use all customer trades in the month. At the end of each month, we identify dealers with eigenvector centrality scores above the 95th percentile as core dealers and the rest as peripheral dealers. Panel D shows the probability that a dealer who provided immediacy this exclusion month also provides immediacy within the next *m* exclusion months. We define immediacy provision as dealers that buy excluded bonds from customers on event days -3 to 0. We report the probability over various horizons for core and peripheral dealers.

Panel A: Number of dealers per month

	Mean	SD	P10	P50	P90
Maturity exclusions	47	14	29	46	66
Downgrade exclusions	25	28	3	16	56
All corporate bonds	1,023	142	830	1,033	1,217

Panel B: Dealer centrality

	Mean	SD	P10	P50	P90
Maturity exclusions	0.50	0.27	0.10	0.51	0.86
Downgrade exclusions	0.52	0.26	0.18	0.52	0.84
All corporate bonds	0.09	0.17	0.00	0.02	0.31

Panel C: Core dealer share of customer volume

	Mean	SD	P10	P50	P90
Maturity exclusions	0.75	0.15	0.53	0.79	0.92
Downgrade exclusions	0.75	0.22	0.47	0.82	1.00
All corporate bonds	0.73	0.06	0.64	0.73	0.80

Panel D: Dealer persistence

	Core				Peripheral			
Trade within $(0,m]$	$m = 1$	$m = 3$	$m = 6$	$m = 12$	$m = 1$	$m = 3$	$m = 6$	$m = 12$
Maturity exclusions	0.78	0.92	0.96	0.97	0.41	0.58	0.67	0.75
Downgrade exclusions	0.44	0.73	0.86	0.91	0.15	0.32	0.45	0.54

Table 2.5: Trading with core versus peripheral dealers

Panel A presents coefficient estimates from the time-series regression:

$$Peripheral\ ratio_m = \beta_0 + \beta_1 Immediacy_m + \epsilon_m$$

where $Peripheral\ ratio_m$ is the number of peripheral dealers out of all dealers that buy excluded bonds from customers on event days -3 to 0 in month m. $Immedaicy_m$ is either (1) the percentage of the index excluded, (2) the aggregate dealer buy volume from customers over event days -3 to 0 measured in \$billions, or (3) the aggregate inventory buildup over event days -3 to 0 measured in \$billions. We use robust standard errors and report t-statistics in parenthesis. Panel B presents coefficient estimates from the trade-level probit regression for peripheral dealer buys ($Peripheral\ buy_{ijt} = 1$) versus core dealer buys ($Peripheral\ buy_{ijt} = 0$) given that a dealer buys from customers on event days -3 to 0:

$$Pr(Peripheral\ buy_{ijt} | Dealer\ buy) = \Phi\left(\beta Core\ inv_t + \eta Inv_{it} + \gamma Log(Trade\ size_{ijt}) + \delta + \epsilon_{ijt}\right)$$

where $Core\ inv_t$ is the aggregate core dealer inventory of excluded bonds before the current trade. Inv_{it} is the inventory buildup of dealer i before the current trade, $Trade\ size_{ijt}$ is measured in dollars. All regressions include either month fixed effects δ_t or bond-times-month fixed effects δ_{jt}. The sample period is from July 2002 to August 2018. Standard errors are clustered by bond issuer and month with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Panel A: Ratio of peripheral dealers out of all dealers

	Maturity exclusions			Downgrade exclusions		
% of index excluded	0.112***			0.105***		
	(4.67)			(3.23)		
Dealer buy volume		0.065***			0.113***	
		(9.40)			(6.41)	
Inventory buildup			0.117***			0.310***
			(8.31)			(6.44)
Intercept	0.382***	0.411***	0.421***	0.375***	0.371***	0.382***
	(22.53)	(51.91)	(53.50)	(21.29)	(21.93)	(23.16)
Adj. R^2	0.115	0.264	0.192	0.084	0.120	0.068
Observations	194	194	194	156	156	156

Panel B: Probability that a peripheral dealer buys from customers

	Maturity exclusions		Downgrade exclusions	
Aggregate core inventory	0.307***	0.389***	0.225***	0.233***
	(5.98)	(6.00)	(3.23)	(3.17)
Dealer inventory	-5.967***	-7.032***	-1.547**	-1.311*
	(-7.70)	(-7.37)	(-1.98)	(-1.81)
Log(Trade size)	-0.029***	-0.028***	-0.088***	-0.091***
	(-4.91)	(-4.18)	(-5.95)	(-6.21)
Fixed effects	Month	Bond×month	Month	Bond×month
Months (clusters)	194	194	143	140
Issuers (clusters)	1,211	919	420	321
Bonds	5,170	3,610	1,181	892
Observations	49,436	41,318	24,614	23,300

Table 2.6: Cumulative dealer inventory around index exclusions

This table shows the average cumulative dealer inventory for core and peripheral dealers scaled by the total nominal size of bonds excluded at the event. The average scaled inventory is measured in percent, event day 0 is the exclusion date, and event time is measured in trading days. At the end of each month, we rank dealers based on eigenvector centrality score and define the top 5 percentile as core and the rest as peripheral dealers. For each event day in a given month, we first compute the aggregate daily inventory change as the difference between the aggregate dealer buying and selling volume across all excluded bonds. Next, we set the inventory level at the beginning of event day -50 to $0, cumulate the daily inventory change over time, and scale by the total nominal size of bonds excluded in the same month. Finally, we compute the average scaled cumulative inventory across all months by dealer type. We exclude dealers that do not buy from customers on event days -3 to 0.

	Maturity exclusions				**Downgrade exclusions**			
	Core		Peripheral		Core		Peripheral	
Event day	Inventory	Fraction	Inventory	Fraction	Inventory	Fraction	Inventory	Fraction
-50	0.00	0.00	0.01	0.02	0.00	0.00	0.00	-0.01
-40	0.04	0.03	0.01	0.02	0.04	0.03	0.04	0.09
-30	0.06	0.04	-0.01	-0.02	0.11	0.08	0.05	0.13
-20	0.15	0.11	0.01	0.04	0.10	0.07	0.08	0.19
-10	0.12	0.09	0.03	0.09	0.38	0.27	0.09	0.21
-9	0.10	0.08	0.01	0.05	0.40	0.29	0.09	0.22
-8	0.11	0.08	0.02	0.07	0.43	0.30	0.09	0.21
-7	0.10	0.07	0.01	0.04	0.45	0.32	0.10	0.24
-6	0.10	0.08	0.01	0.04	0.45	0.32	0.10	0.24
-5	0.12	0.09	0.02	0.06	0.50	0.36	0.12	0.30
-4	0.19	0.14	0.03	0.12	0.57	0.41	0.18	0.43
-3	0.50	0.38	0.11	0.37	0.67	0.48	0.22	0.53
-2	0.87	0.66	0.16	0.54	0.79	0.56	0.24	0.59
-1	0.92	0.70	0.18	0.61	0.98	0.70	0.30	0.73
0	1.32	1.00	0.29	1.00	1.40	1.00	0.41	1.00
1	1.23	0.94	0.28	0.97	1.36	0.97	0.39	0.95
2	1.13	0.86	0.26	0.88	1.39	1.00	0.37	0.91
3	1.03	0.78	0.23	0.81	1.37	0.98	0.39	0.97
4	0.96	0.73	0.22	0.76	1.34	0.96	0.40	0.99
5	0.91	0.69	0.21	0.71	1.32	0.94	0.39	0.97
6	0.86	0.65	0.20	0.68	1.30	0.93	0.39	0.97
7	0.80	0.61	0.19	0.64	1.22	0.87	0.40	0.98
8	0.74	0.57	0.17	0.60	1.21	0.86	0.40	0.98
9	0.70	0.53	0.16	0.56	1.22	0.87	0.41	1.01
10	0.66	0.50	0.15	0.53	1.28	0.92	0.40	0.99
20	0.41	0.31	0.10	0.34	1.12	0.80	0.31	0.77
30	0.28	0.21	0.10	0.33	0.99	0.70	0.35	0.86
40	0.14	0.11	0.06	0.19	0.91	0.65	0.34	0.83
50	0.07	0.05	0.03	0.10	0.82	0.59	0.34	0.85
100	-0.10	-0.08	0.00	0.00	0.48	0.35	0.27	0.66

Table 2.7: Speed of inventory adjustment

Panel A presents coefficient estimates from the regression:

$$\beta_{im} = \alpha + \theta Centrality_{im} + \delta_m + \epsilon_{im}$$

where β_{im} is the estimated speed of inventory adjustment for dealer i in month m. $Centrality_{im}$ is the eigenvector centrality score based on all interdealer transactions during the month. The second and fourth column include month fixed effects δ_m. For each month, we estimate the speed of inventory adjustment for every dealer with a non-negative cumulative inventory buildup of excluded bonds over event days -3 to 0 using the regression:

$$I_t - I_{t-1} = \beta(I_{t-1} - \alpha_0 - \alpha_1 I_{[t \geq 20]})$$

where I_t is the cumulative inventory across all excluded bonds for a given dealer on event day t, α_0 represents the target level of inventory before the exclusion event $[t \in \{-50, \cdots, -20\}]$, and α_1 represents the change in target level of inventory after the exclusion event $[t \in \{20, \cdots, 100\}]$. Event day 0 is the exclusion date. The t-statistics are reported in parenthesis with the convention *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. Panel B shows the average inventory half-life for dealer quartiles based on eigenvector centrality scores. The half-life quantity is obtained using the formula $-\ln(2)/\ln(1+\bar{\beta})$.

Panel A: Inventory adjustment speed

	Maturity exclusions		Downgrade exclusions	
Centrality	-0.10***	-0.10***	-0.06***	-0.06***
	(-16.72)	(-15.54)	(-7.17)	(-6.29)
Constant	-0.08***		-0.08***	
	(-25.05)		(-17.30)	
Month FE	No	Yes	No	Yes
Adj. R^2	0.03	0.04	0.01	0.03
Months	193	193	151	148
Observations	10,449	10,449	4,144	4,141

Panel B: Inventory half-life

Quartile	Mean	Median	Mean	Median
1 Low centrality	8.31	22.76	8.31	22.76
2	4.60	11.20	5.95	13.51
3	4.27	8.31	4.60	9.55
4 High centrality	4.27	7.35	5.95	9.55

Table 2.8: Centrality spread for customer–dealer trades

This table presents coefficient estimates from the regression:

$$Price_{ijt} = \beta Centrality_{it} + \gamma Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

where $Price_{ijt}$ is the volume-weighted dealer buy or sell price measured in basis points for dealer i, bond j, and day t. All prices are from the dealer's perspective. For index exclusions, we calculate the dealer buy price over event days -3 to 0 where event day 0 is the exclusion date. We compute the dealer sell price on each event day $t \in \{1, \ldots, 30\}$ after the exclusion date. In the sample of all corporate bonds, we compute dealer-bond specific volume-weighted buy and sell prices on each trading day. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. $Volume_{ijt}$ is the cumulative volume of the transactions used to compute the volume-weighted dealer-bond specific price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to August 2018. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions		All corporate bonds	
	Buy from customer	Sell to customer	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Centrality	4.090***	-5.841***	32.295	-25.562***	10.912***	-18.588***
	(4.32)	(-9.77)	(0.95)	(-6.63)	(18.69)	(-25.91)
Log(Volume)	2.592***	-2.581***	9.854***	-20.090***	5.119***	-10.067***
	(14.20)	(-14.82)	(3.22)	(-10.96)	(17.57)	(-29.45)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.995	0.992	0.984	0.993	0.998	0.997
Issuers (clusters)	1,056	970	336	350	4,475	4,548
Days (clusters)	194	3,690	145	1,954	4,064	4,078
Bonds	4,346	4,065	944	947	26,675	29,331
Observations	17,156	52,997	5,076	24,615	4,226,371	5,617,312

Table 2.9: Centrality spread for interdealer trades

This table presents coefficient estimates from the regression:

$$Price_{jt} = \beta_1 Buyer\ centrality_t + \beta_2 Seller\ centrality_t + \gamma Log(Volume_{jt}) + \delta_{jt} + \epsilon_{jt}$$

where $Price_{jt}$ is the volume-weighted interdealer price measured in basis points between the buying and selling dealer for bond j on day t. For index exclusions, we calculate the interdealer price on each event day $t \in \{-3, \dots, 30\}$ where event day 0 is the exclusion date. In the sample of all corporate bonds, we compute interdealer prices on each trading day. $Buyer\ centrality_t$ and $Seller\ centrality_t$ denote the eigenvector centrality scores of the buying and selling dealer based on all interdealer transactions during the exclusion month. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. $Volume_{jt}$ is the cumulative volume of the transactions used to compute the volume-weighted price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to August 2018. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions	Downgrade exclusions	All corporate bonds
Buyer centrality	-5.727***	-13.778***	-7.027***
	(-9.96)	(-2.97)	(-13.60)
Seller centrality	9.622***	14.396***	6.998***
	(10.00)	(4.52)	(15.64)
Log(Volume)	-1.081***	0.467	-2.062***
	(-3.89)	(0.25)	(-13.00)
Bond×day FE	Yes	Yes	Yes
Adj. R^2	0.995	0.997	0.998
Issuers (clusters)	1,079	372	4,808
Days (clusters)	3,844	2,594	4,065
Bonds	4,400	1,078	35,603
Observations	80,622	69,485	9,815,924

Table 2.10: Prearranged trades

This table presents summary statistics for prearranged trades defined as trades where a dealer buys and sells the same bond with the same volume within 60 seconds. We divide prearranged trades into four groups based on counterparty type (C denotes customer and D denotes dealer) and the naming convention reflects how a bond travels from the seller through the prearranging dealer to the buyer. For index exclusions, we identify prearranged trades on event days -3 to 0 where event day 0 is the exclusion date. In the sample of all corporate bonds, we identify prearranged trades on all trading days. Panel A shows the average ratio of prearranged customer volume to the total customer volume. At the end of each month, we identify dealers with eigenvector centrality scores above the 95th percentile as core dealers and the rest as peripheral dealers. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. The ratios are time-series averages across months. Panel B shows sample averages of markups measured in basis points from the prearranging dealer's point of view, trade sizes measured in $millions, and eigenvector centrality scores of the selling dealer, the prearranging dealer, and the buying dealer. Trade sizes are at least $100,000 and the sample period is from July 2002 to August 2018.

Panel A: Prearranged customer volume out of total customer volume (%)

	Maturity exclusions	Downgrade exclusions	All corporate bonds
Peripheral	11.04	17.16	12.00
Core	4.72	9.61	5.50

Panel B: Summary statistics

	CDC			DDD		
	Maturity	Downgrade	All bonds	Maturity	Downgrade	All bonds
Markup	4.81	88.98	25.61	1.86	10.03	5.62
Trade size	3.55	3.93	2.22	1.01	0.74	0.85
Seller centrality				0.67	0.65	0.63
Prearranging centrality	0.63	0.52	0.52	0.62	0.54	0.53
Buyer centrality				0.41	0.60	0.57
Observations	925	637	518,140	1,109	1,049	1,240,760

	CDD			DDC		
	Maturity	Downgrade	All bonds	Maturity	Downgrade	All bonds
Markup	4.82	31.95	22.30	13.89	75.31	41.37
Trade size	2.32	0.51	0.59	1.26	0.76	0.57
Seller centrality				0.75	0.69	0.71
Prearranging centrality	0.63	0.46	0.44	0.54	0.43	0.47
Buyer centrality	0.78	0.71	0.70			
Observations	1,523	486	609,904	3,231	968	1,376,612

Table 2.11: Centrality spread for prearranged trades

This table presents coefficient estimates from the regression:

$$Markup_{ijt} = \beta Centrality_{it} + \gamma Log(Trade\ size_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

where $Markup_{ijt}$ is measured in basis points for the prearranging dealer i, bond j on day t. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month for each dealer in the prearranged trade. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. For index exclusions, we use prearranged trades on event days -3 to 0 where event day 0 is the exclusion date. In the sample of all corporate bonds, we use prearranged trades on all trading days. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to August 2018. We cluster standard errors by bond issuer and month for index exclusions and by bond issuer and trading day in the sample of all corporate bonds. We report t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	CDC			DDD		
	Maturity	Downgrade	All bonds	Maturity	Downgrade	All bonds
Seller centrality				0.296	-3.197	0.983***
				(0.23)	(-0.79)	(4.21)
Prearranging centrality	3.745	-51.993	-0.534	-4.317**	-7.843	-6.044***
	(0.72)	(-1.63)	(-0.27)	(-2.49)	(-1.33)	(-7.04)
Buyer centrality				0.999	2.724	1.520***
				(1.61)	(1.07)	(5.30)
Log(Trade size)	-0.141	-4.104	-0.955**	-0.756*	-0.747	0.216**
	(-1.19)	(-0.49)	(-2.50)	(-1.91)	(-0.82)	(2.03)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.706	0.302	0.638	0.279	0.508	0.441
Issuers (clusters)	131	85	3,253	119	93	3,109
Months/days (clusters)	61	53	3,979	90	63	4,039
Bonds	148	132	10,354	211	188	15,372
Observations	352	411	80,176	551	850	432,926

	CDD			DDC		
	Maturity	Downgrade	All bonds	Maturity	Downgrade	All bonds
Seller centrality				6.783***	22.145	12.722***
				(2.88)	(1.41)	(7.72)
Prearranging centrality	-12.585***	-51.123***	-20.834***	-4.327*	-26.727	-26.224***
	(-2.65)	(-3.23)	(-15.61)	(-1.77)	(-1.18)	(-15.76)
Buyer centrality	-3.691	-7.659	3.539***			
	(-0.78)	(-0.66)	(3.77)			
Log(Trade size)	-0.659**	-3.633	-5.603***	-2.279***	-17.356***	-11.721***
	(-2.39)	(-0.95)	(-9.84)	(-6.06)	(-3.28)	(-16.65)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.447	0.179	0.477	0.315	0.291	0.548
Issuers (clusters)	199	53	2,150	339	90	2,886
Months/days (clusters)	82	45	3,882	144	64	4,040
Bonds	295	95	9,067	700	178	16,058
Observations	813	300	96,390	2,234	769	417,355

Table 2.12: Inventory dynamics by subperiod

This table shows the average cumulative dealer inventory scaled by the total nominal size of bonds excluded at the event. We use four subperiods: pre-crisis is from July 2002 to June 2007, crisis is from July 2007 to December 2009, post-crisis is from January 2010 to June 2014, and the Volcker period is from July 2014 to August 2018. The average scaled inventory is measured in percent, event day 0 is the exclusion date, and event time is measured in trading days. For each event day in a given month, we first compute the aggregate daily inventory change as the difference between the aggregate dealer buying and selling volume across all excluded bonds. Next, we set the inventory level at the beginning of event day -50 to $0, cumulate the daily inventory change over time, and scale by the total nominal size of bonds excluded in the same month. Finally, we compute the average scaled cumulative inventory across all months for each subperiod. We exclude dealers that do not buy from customers on event days -3 to 0.

	Pre-crisis		Crisis		Post-crisis		Volcker	
Event day	Inventory	Fraction	Inventory	Fraction	Inventory	Fraction	Inventory	Fraction
Panel A: Maturity exclusions								
-50	0.01	0.01	-0.04	-0.04	0.02	0.01	-0.01	0.00
-10	0.11	0.08	0.15	0.17	0.06	0.04	0.28	0.12
-5	0.05	0.04	0.21	0.24	0.12	0.08	0.23	0.09
0	1.33	1.00	0.89	1.00	1.58	1.00	2.39	1.00
5	1.13	0.85	0.55	0.61	0.90	0.57	1.67	0.70
10	0.82	0.62	0.33	0.37	0.56	0.35	1.37	0.57
20	0.50	0.38	0.21	0.23	0.25	0.16	0.98	0.41
30	0.33	0.25	0.18	0.20	0.01	0.01	0.93	0.39
40	0.11	0.08	0.06	0.06	-0.14	-0.09	0.77	0.32
50	-0.03	-0.02	-0.03	-0.04	-0.25	-0.16	0.69	0.29
100	-0.35	-0.26	-0.07	-0.08	-0.43	-0.27	0.53	0.22
Panel B: Downgrade exclusions								
-50	0.00	0.00	-0.05	-0.04	0.01	0.01	0.00	0.00
-10	0.78	0.29	0.29	0.24	0.13	0.10	0.40	0.30
-5	0.96	0.36	0.43	0.36	0.25	0.20	0.57	0.42
0	2.66	1.00	1.19	1.00	1.26	1.00	1.33	1.00
5	2.47	0.93	1.00	0.84	1.25	0.99	1.35	1.01
10	2.57	0.97	1.08	0.91	0.98	0.78	1.31	0.98
20	2.14	0.80	1.01	0.84	0.66	0.53	1.29	0.97
30	2.11	0.79	1.01	0.84	0.34	0.27	1.23	0.93
40	1.92	0.72	1.07	0.90	0.15	0.12	1.28	0.96
50	1.76	0.66	1.17	0.98	0.06	0.05	1.23	0.92
100	1.53	0.58	0.90	0.75	-0.96	-0.77	1.06	0.79

Table 2.13: Network centrality by subperiod

Panel A presents coefficient estimates from the time-series regression:

$$VW\ centrality_m = \beta_0 + \beta_1 Crisis_m + \beta_2 Post\text{-}crisis_m + \beta_3 Volcker_m + \epsilon_{im}$$

where $VW\ centrality_m$ is the volume-weighted average eigenvector centrality score in month m. We compute the centrality score for each dealer based on all interdealer transactions during the exclusion month. For index exclusions, we weigh centrality scores by the buy volume from customers over event days [-3, 0] where event day 0 is the exclusion date. In the sample of all corporate bonds, we weigh centrality scores by the buy volume from customers over the entire month. We use the pre-crisis period from July 2002 to June 2007 from as the omitted group and include indicator variables for the crisis period from July 2007 to December 2009, the post-crisis period from January 2010 to June 2014, and the Volcker period from July 2014 to August 2018. We use robust standard errors and report t-statistics in parenthesis. Panel B presents coefficient estimates from the panel regression:

$$Centrality_{im} = \beta_0 + \beta_1 Crisis_m + \beta_2 Post\text{-}crisis_m + \beta_3 Volcker_m + \delta_i + \epsilon_{im}$$

where $Centrality_{im}$ is the eigenvector centrality score for dealer i in month m. We use the pre-crisis period as the omitted group and include indicator variables for the remaining time periods together with dealer fixed effects δ_i. For index exclusions, we consider dealers that buy from customers on event days -3 to 0 only. Standard errors are clustered by dealer and month with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions	Downgrade exclusions	All corporate bonds
Panel A: Volume-weighted network centrality			
Pre-crisis (β_0)	0.522***	0.537***	0.514***
	(50.42)	(32.54)	(58.25)
Crisis	0.027	-0.021	0.005
	(1.20)	(-0.74)	(0.49)
Post-crisis	0.173***	0.089***	0.160***
	(11.55)	(3.19)	(13.57)
Volcker	0.263***	0.191***	0.228***
	(20.18)	(6.73)	(21.37)
Adj. R^2	0.652	0.277	0.736
Observations	194	156	194
Panel B: Within-dealer variation in centrality			
Pre-crisis (β_0)	0.464***	0.448***	0.080***
	(29.35)	(27.35)	(40.34)
Crisis	-0.020	-0.030*	0.005*
	(-1.28)	(-1.89)	(1.93)
Post-crisis	0.069***	0.084***	0.022***
	(3.20)	(3.27)	(6.79)
Volcker	0.097***	0.110***	0.029***
	(3.45)	(3.64)	(6.60)
Dealer FE	Yes	Yes	Yes
Adj. R^2	0.873	0.891	0.863
Months (clusters)	194	156	194
Observations	8,730	3,539	198,044

Table 2.14: Centrality spread by subperiod

Panel A presents coefficient estimates for customer–dealer trades from the regression:

$$Price_{ijt} = \sum_s \beta_s Centrality_{it} \mathbb{1}_s + \gamma Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

and Panel B presents coefficient estimates for interdealer trades from the regression:

$$Price_{jt} = \sum_s \beta_s Buyer\ centrality_t \mathbb{1}_s + \sum_s \eta_s Seller\ centrality_t \mathbb{1}_s + \gamma Log(Volume_{jt}) + \delta_{jt} + \epsilon_{jt}$$

where $\mathbb{1}_s$ is an indicator variable that takes a value of 1 in subperiod s. We use four subperiods: pre-crisis is from July 2002 to June 2007, crisis is from July 2007 to December 2009, post-crisis is from January 2010 to June 2014, and the Volcker period is from July 2014 to August 2018. The remaining variables are defined in Table 2.8 for customer–dealer trades and Table 2.9 for interdealer trades. We do not report coefficient estimates on $Log(Volume_{jt})$. All regressions include bond-times-day fixed effects δ_{jt}. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions		All corporate bonds	
Panel A: Centrality spread for customer–dealer trades						
	Buy from customer	Sell to customer	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Pre-crisis	6.512**	-12.268***	32.659	-29.185***	13.995***	-25.065***
	(2.57)	(-12.35)	(1.51)	(-3.56)	(10.38)	(-14.41)
Crisis	10.031**	-11.338***	75.600	-15.165	9.201***	-23.662***
	(2.30)	(-3.38)	(0.64)	(-0.87)	(7.32)	(-14.08)
Post-crisis	5.807***	-4.933***	37.890**	-20.713**	12.593***	-19.727***
	(2.94)	(-4.49)	(2.09)	(-2.25)	(12.83)	(-14.36)
Volcker	-0.198	-2.538***	-14.708	-26.910***	7.777***	-12.108***
	(-0.23)	(-3.88)	(-1.40)	(-5.15)	(12.73)	(-16.34)
Adj. R^2	0.995	0.992	0.984	0.993	0.998	0.997
Observations	17,156	52,997	5,076	24,615	4,226,371	5,617,312
t-test (Post<Pre)	-0.22	4.76***	0.19	0.68	-0.83	2.23**
t-test (Volcker<Pre)	-2.47**	7.95***	-2.10**	0.22	-3.97***	6.37***

Panel B: Centrality spread for interdealer trades						
	Buyer centrality	Seller centrality	Buyer centrality	Seller centrality	Buyer centrality	Seller centrality
Pre-crisis	-5.626***	5.755***	-33.234***	22.417***	-11.773***	8.208***
	(-2.84)	(3.19)	(-7.39)	(6.22)	(-7.39)	(7.71)
Crisis	-17.341***	33.324***	-42.039	25.083	-22.167***	28.427***
	(-8.84)	(8.02)	(-1.16)	(1.16)	(-13.51)	(15.95)
Post-crisis	- 2.911***	5.779***	-2.016	7.752***	-3.841***	3.978***
	(-4.28)	(4.51)	(-0.59)	(6.83)	(-10.39)	(12.10)
Volcker	-2.651***	3.419***	-1.144	11.611***	-2.867***	3.078***
	(-11.14)	(8.47)	(-0.74)	(4.54)	(-11.21)	(12.89)
Adj. R^2	0.995		0.997		0.998	
Observations	80,622		69,485		9,815,924	
t-test (Post<Pre)	1.30	0.01	4.26***	-3.98***	4.75***	-3.79***
t-test (Volcker<Pre)	1.53	-1.24	4.82***	-2.57**	5.46***	-4.69***

Table 2.15: Alternative explanations for the customer–dealer centrality spread

This table presents coefficient estimates from the regression:

$$Price_{ijt} = \beta Centrality_{it} + \gamma Log(Volume_{ijt}) + \eta Proxy_{it} + \delta_{jt} + \epsilon_{ijt}$$

where $Price_{ijt}$ is the volume-weighted dealer buy or sell price measured in basis points for dealer i, bond j, and day t. All prices are from the dealer's perspective. For index exclusions, we calculate the dealer buy price over event days -3 to 0 where event day 0 is the exclusion date. We compute the dealer sell price on each event day $t \in \{1, ..., 30\}$ after the exclusion date. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. $Volume_{ijt}$ is the cumulative volume of the transactions used to compute the volume-weighted dealer-bond specific price. $Proxy_{it}$ is either (1) the dealer's share of total order flow, (2) the number of block trades (trade size of at least 5 million) for each dealer out of all dealer buys from customers, or (3) the dealer's share of total dealer buy volume from customers. All proxies are computed at the dealer-month level across all excluded bonds (maturity and downgrade exclusions separately) using trades on event days -3 to 0. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to August 2018. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Buy from customer			Sell to customer		
Panel A: Maturity exclusions						
Centrality	4.419***	4.378***	4.110***	-4.565***	-4.296***	-4.443***
	(4.56)	(4.46)	(4.31)	(-7.05)	(-6.53)	(-6.93)
Log(Volume)	2.683***	2.676***	2.531***	-2.403***	-2.343***	-2.241***
	(14.89)	(14.86)	(14.27)	(-13.95)	(-13.65)	(-13.27)
Order flow	-4.808**			-18.489***		
	(-2.58)			(-10.14)		
Block trades		0.905			-10.356***	
		(1.25)			(-14.06)	
Dealer market share			-3.767**			-21.904***
			(-2.10)			(-11.49)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.995	0.995	0.995	0.992	0.992	0.992
Observations	17,156	17,156	17,156	52,997	52,997	52,997
Panel B: Downgrade exclusions						
Centrality	32.945	33.358	32.855	-24.194***	-23.885***	-23.640***
	(0.96)	(0.97)	(0.97)	(-6.04)	(-5.97)	(-6.26)
Log(Volume)	10.383***	10.691***	8.123***	-19.627***	-19.475***	-18.506***
	(3.78)	(3.90)	(3.11)	(-9.55)	(-9.50)	(-8.36)
Order flow	-17.972			-23.569		
	(-0.64)			(-0.97)		
Block trades		24.498*			-29.338*	
		(1.96)			(-1.88)	
Dealer market share			-24.832			-28.794
			(-0.98)			(-1.33)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.984	0.984	0.984	0.993	0.993	0.993
Observations	5,076	5,076	5,076	24,615	24,615	24,615

Table 2.16: Alternative explanations for the interdealer centrality spread

This table presents coefficient estimates from the regression:

$$Price_{jt} = \beta_1 Buyer\ centrality_t + \beta_2 Seller\ centrality_t + \gamma Log(Volume_{jt}) + \eta_1 Buyer\ proxy_t + \eta_2 Seller\ proxy_t + \delta_{jt} + \epsilon_{jt}$$

where $Price_{jt}$ is the volume-weighted interdealer price measured in basis points between the buying and selling dealer for bond j on day t. For index exclusions, we calculate the interdealer price on each event day $t \in \{-3, \ldots, 30\}$ where event day 0 is the exclusion date. $Buyer\ centrality_t$ and $Seller\ centrality_t$ denote the eigenvector centrality scores of the buying and selling dealer based on all interdealer transactions during the exclusion month. $Volume_{jt}$ is the cumulative volume of the transactions used to compute the volume-weighted price. $Buyer\ proxy_t$ and $Seller\ proxy_t$ are either (1) the dealer's share of total order flow, (2) the number of block trades (trade size of at least 5 million) for each dealer out of all dealer buys from customers, or (3) the dealer's share of total dealer buy volume from customers. All proxies are computed at the dealer-month level across all excluded bonds (maturity and downgrade exclusions separately) using trades on event days -3 to 0. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to August 2018. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions			Downgrade exclusions		
Buyer centrality	-6.083***	-5.892***	-5.958***	-15.709***	-18.152***	-17.019***
	(-9.08)	(-9.74)	(-9.18)	(-3.18)	(-3.81)	(-3.44)
Seller centrality	10.572***	10.182***	10.487***	16.505***	17.123***	17.704***
	(10.53)	(10.51)	(10.45)	(5.52)	(5.42)	(5.59)
Log(Volume)	-0.997***	-0.983***	-0.979***	0.444	-0.182	0.432
	(-3.56)	(-3.50)	(-3.52)	(0.26)	(-0.12)	(0.25)
Buyer order flow	9.947***			33.152**		
	(2.66)			(2.53)		
Seller order flow	-11.441***			-29.450***		
	(-3.89)			(-3.59)		
Buyer block trades		1.959*			30.678***	
		(1.70)			(3.13)	
Seller block trades		-3.428***			-3.848	
		(-4.49)			(-0.48)	
Buyer market share			7.059**			44.360***
			(2.19)			(3.22)
Seller market share			-9.921***			-33.553***
			(-3.59)			(-5.32)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.995	0.995	0.995	0.997	0.997	0.997
Observations	80,622	80,622	80,622	69,485	69,485	69,485

Table 2.17: Trade size and dealer centrality

This table presents coefficient estimates from the regression:

$$Log(Trade\ size_{ijt}) = \sum_{s} \beta_s Centrality_{it} \mathbb{1}_s + \delta_{jt} + \epsilon_{ijt}$$

where $Trade\ size_{ijt}$ is for dealer i, bond j, and day t. For index exclusions, we use transactions on event days -3 to 0 where event day 0 is the exclusion date. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. $\mathbb{1}_s$ is an indicator variable that takes a value of one in time period s. We use four time periods: the pre-crisis period is from July 2002 to June 2007, the crisis period is from July 2007 to December 2009, the post-crisis period is from January 2010 to June 2014, and the Volcker period is from July 2014 to August 2018. All regressions include bond-times-day fixed effects δ_{jt}. We exclude trade sizes below $\$100,000$. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions		All corporate bonds	
	Buy from customer	Sell to customer	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Centrality*Pre-crisis	-0.809***	-0.467***	0.034	0.377***	-0.316***	-0.385***
	(-7.58)	(-7.70)	(0.23)	(2.75)	(-7.38)	(-7.67)
Centrality*Crisis	-0.181	-0.106	-0.297	0.087	-0.119***	-0.021
	(-1.19)	(-1.02)	(-0.89)	(0.44)	(-2.67)	(-0.56)
Centrality*Post-crisis	0.198*	0.030	0.345*	0.541***	0.220***	0.242***
	(1.78)	(0.38)	(1.90)	(5.25)	(10.58)	(11.81)
Centrality*Volcker	1.227***	0.629***	0.827***	0.611***	0.360***	0.455***
	(9.85)	(11.82)	(4.72)	(4.81)	(15.61)	(14.78)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	-0.024	0.228	0.110	0.374	0.249	0.282
Issuers (clusters)	1,091	966	357	349	4,598	4,662
Days (clusters)	768	3,690	522	1,954	4,067	4,082
Observations	30,561	63,169	12,014	31,827	5,413,629	7,141,579

Table 2.18: Customer heterogeneity and the centrality spread

This table presents coefficient estimates on centrality from the regression in Table 2.8 when dealers buy excluded bonds from customers at exclusion (event days -3 to 0). In Panel A, we interact centrality with an indicator variable $High_{jt}$ that takes a value of 1 when bond j has above median customer heterogeneity on day t. We use institutional bond holdings from Refinitiv eMAXX to identify customers that sell excluded bonds around the exclusion date. We measure customer heterogeneity separately for bond funds and for all customer types in eMAXX. For each bond exclusion, we compute (1) the number of selling customers and (2) the standard deviation of customer size based on the aggregate par value of their fixed income holdings. We then use the median of each measure every month to divide excluded bonds into a high and low customer heterogeneity group. Panel B shows the coefficient estimates on centrality after removing trades that could involve other customer types than bond funds. For each bond exclusion, we remove all trade sizes up to the largest (1) actual sell trade on the same day by insurance companies as reported in NAIC and (2) implied sell trade around the exclusion date by other customer types in eMAXX than bond funds or insurance companies. We then estimate the regression in subsamples based on the number of selling fund families per bond exclusion. Panel C presents coefficient estimates on centrality for different event windows. All regressions include bond-times-day fixed effects δ_{jt} and we do not report coefficient estimates on $Log(Volume_{jt})$. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Panel A: Proxies for customer heterogeneity

	Maturity exclusions				Downgrade exclusions			
	Bond funds		All customer types		Bond funds		All customer types	
Proxy:	N sellers	SD size	N sellers	SD size	N sellers	SD size	N sellers	SD size
Centrality*High	-0.882	-1.017	-1.187	1.029	-21.795	-7.274	-68.672	31.952
	(-0.52)	(-0.64)	(-0.67)	(0.63)	(-0.87)	(-0.38)	(-1.08)	(1.38)
Centrality	4.563***	4.584***	4.767***	3.599***	43.954	35.798	72.960	16.733
	(3.09)	(3.62)	(2.93)	(3.55)	(0.97)	(1.02)	(1.04)	(0.48)
Adj. R^2	0.995	0.995	0.995	0.995	0.984	0.984	0.984	0.984
Observations	17,157	17,157	17,157	17,157	5,076	5,076	5,076	5,076

Panel B: Exclude trades that could involve other customers than bond funds

	Maturity exclusions			Downgrade exclusions		
Fund families:	$N \geq 0$	$N \geq 1$	$N = 1$	$N \geq 0$	$N \geq 1$	$N = 1$
Centrality	3.387***	3.440***	10.591***	16.094	21.120	30.216
	(4.18)	(4.18)	(3.40)	(0.92)	(1.20)	(0.83)
Adj. R^2	0.996	0.996	0.994	0.990	0.990	0.995
Bonds	4,133	3,906	388	929	835	101
Observations	15,286	14,666	1,140	4,335	4,061	309

Panel C: Event window length

	Maturity exclusions			Downgrade exclusions		
Event days:	-3 to 0	-2 to 0	-1 to 0	-3 to 0	-2 to 0	-1 to 0
Centrality	4.085***	3.791***	3.970***	32.295	45.219	50.962
	(4.31)	(3.60)	(3.24)	(0.95)	(0.97)	(0.88)
Adj. R^2	0.995	0.995	0.996	0.984	0.983	0.986
Bonds	4,346	3,845	3,032	984	938	829
Observations	17,157	13,364	9,055	5,076	4,403	3,411

Figure 2.1: Network structure

These figures show the core-periphery network structure in the corporate bond market. Panel A presents the inverse distribution function for eigenvector centrality scores. Panel B illustrates the dealer network in a single month where each circle denotes a broker-dealer firm, the size and shade of each circle is proportional to the centrality score, and each line represents a trading relationship.

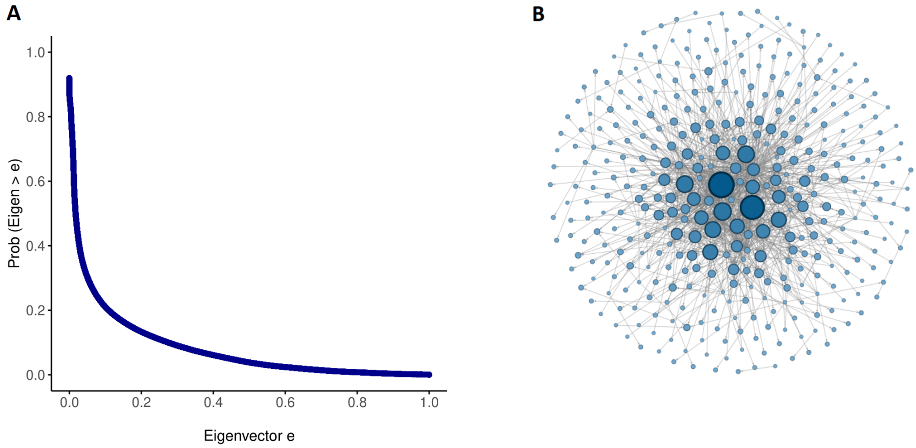


Figure 2.2: Trading activity around index exclusions

This figure shows the average daily trading volume scaled by the total nominal size of bonds excluded at the event. The average scaled volume is measured in percent, event day 0 is the exclusion date, and event time is measured in trading days. We aggregate trading volume across all bonds excluded in a given month and scale by the total nominal size of bonds excluded in the same month. Finally, we compute the average scaled trading volume across all months. Panels A–B present customer–dealer volume and Panels C–D present interdealer volume.

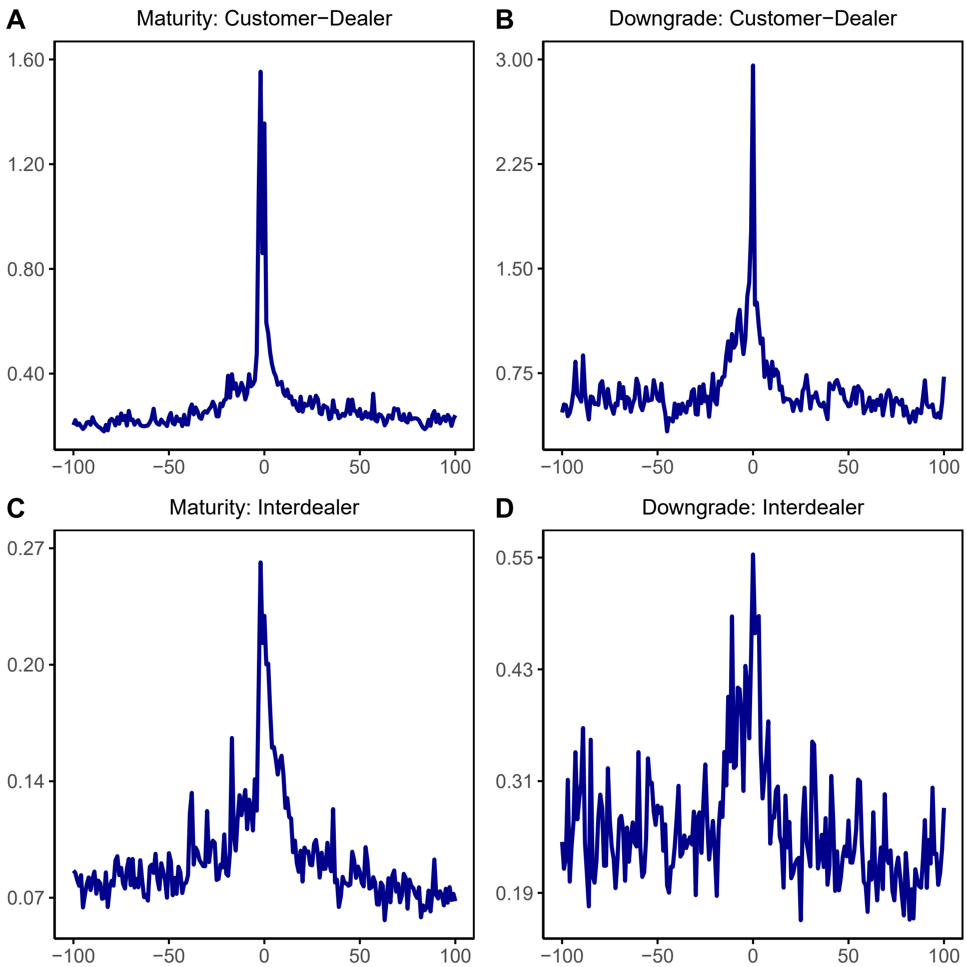


Figure 2.3: Immediacy-providing dealers

This figure presents information on immediacy-providing dealers defined as dealers that buy excluded bonds from customers at exclusion (event days -3 to 0). Panel A shows the number of immediacy-providing dealers in each month by exclusion reason. Panel B shows the fraction of core dealers in each month.

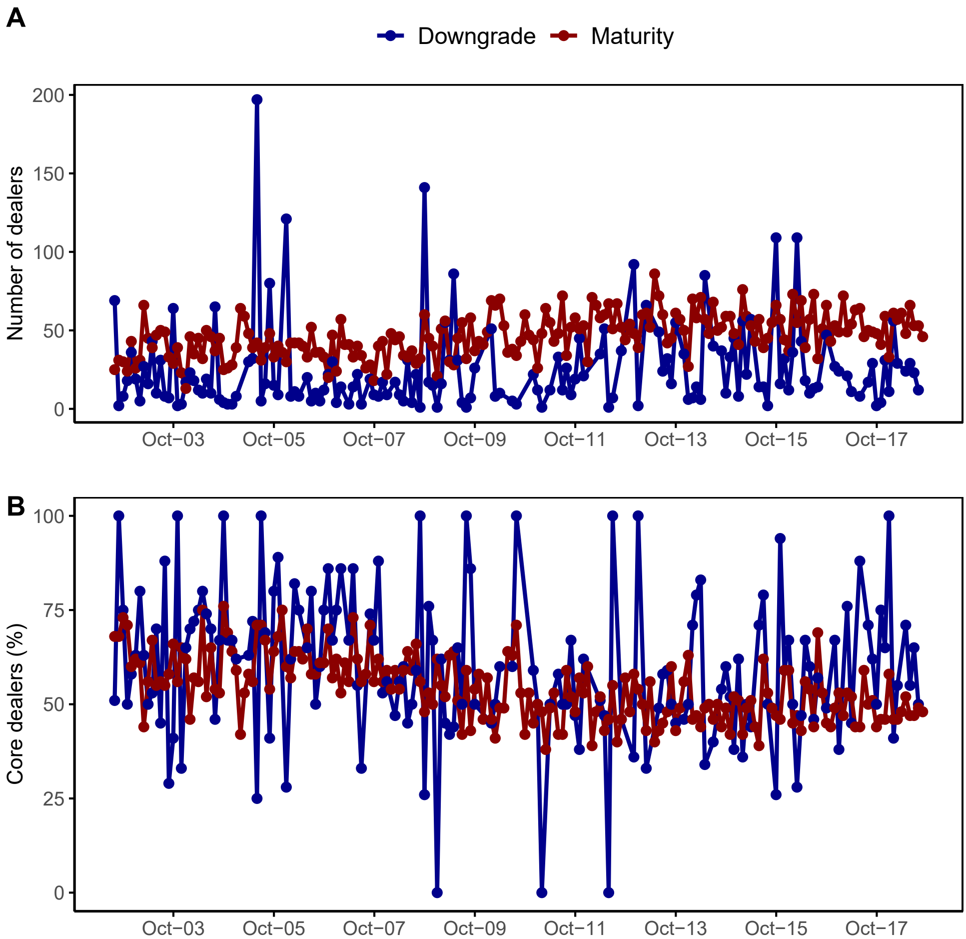


Figure 2.4: Cumulative dealer inventory around index exclusions

This figure shows the average cumulative dealer inventory for core and peripheral dealers scaled by the total nominal size of bonds excluded at the event. The average scaled inventory is measured in percent, event day 0 is the exclusion date, and event time is measured in trading days. At the end of each month, we rank dealers based on eigenvector centrality score and define the top 5 percentile as core and the rest as peripheral dealers. For each event day in a given month, we first compute the aggregate daily inventory change as the difference between the aggregate dealer buying and selling volume across all excluded bonds. Next, we set the inventory at the beginning of event day -50 to $0, cumulate the daily inventory change over time, and scaled by the total nominal size of bonds excluded in the same month. Finally, we compute the average scaled cumulate inventory across all months by dealer type. We exclude dealers that do not buy from customers on event days -3 to 0.

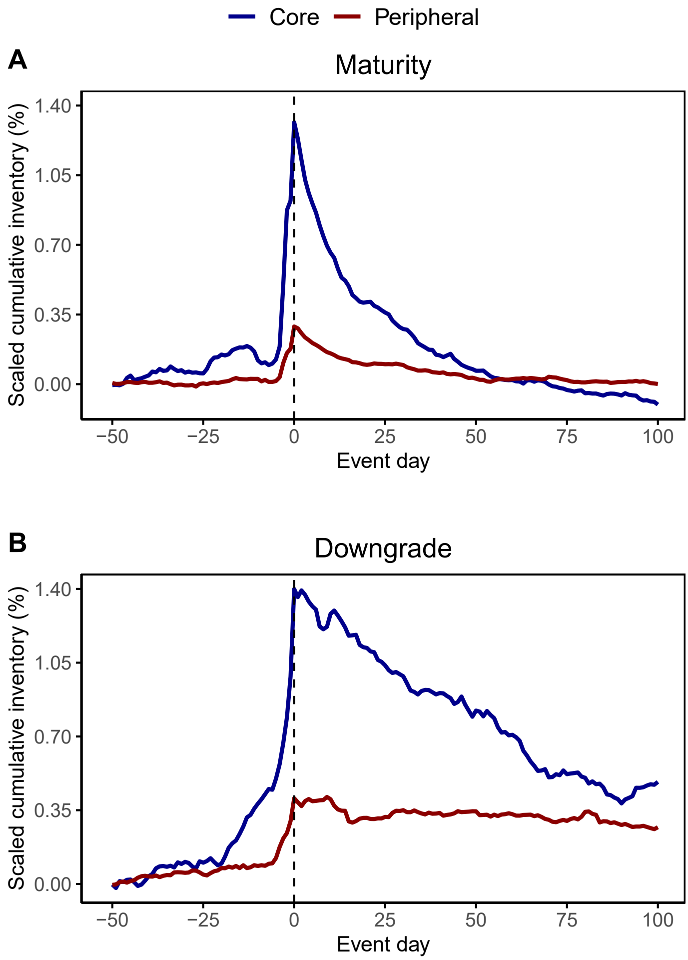
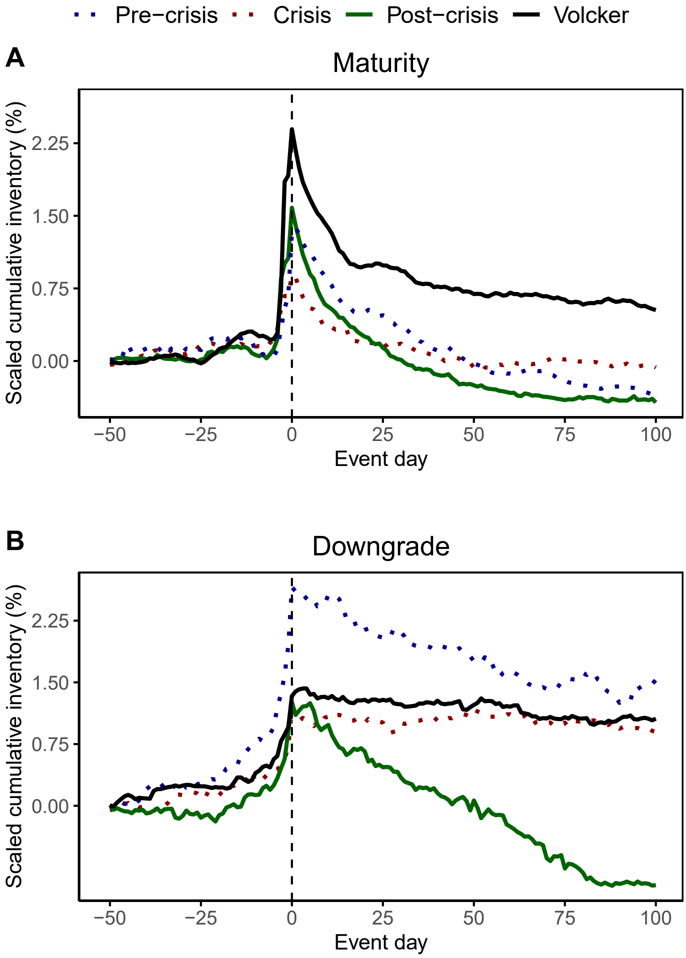


Figure 2.5: Cumulative dealer inventory by subperiod

This figure shows the average cumulative dealer inventory scaled by the total nominal size of bonds excluded at the event. We use four subperiods: pre-crisis is from July 2002 to June 2007, crisis is from July 2007 to December 2009, post-crisis is from January 2010 to June 2014, and the Volcker period is from July 2014 to August 2018. The average scaled inventory is measured in percent, event day 0 is the exclusion date, and event time is measured in trading days. For each event day in a given month, we first compute the aggregate daily inventory change as the difference between the aggregate dealer buying and selling volume across all excluded bonds. Next, we set the inventory level at the beginning of event day -50 to $0, cumulate the daily inventory change over time, and scale by the total nominal size of bonds excluded in the same month. Finally, we compute the average scaled cumulative inventory across all months for each subperiod. We exclude dealers that do not buy from customers on event days -3 to 0.



2.A Huang and Wei (2017) Model

In this Appendix, we derive the centrality spread in the Huang and Wei (2017) model and show the conditions under which index trackers trade with core versus peripheral dealers. We first present the structure of the model before solving for equilibrium prices and quantities in the interdealer and customer-dealer markets. The model has an interdealer centrality premium and a customer-dealer centrality discount consistent with our empirical findings. Dealer market power results in an interdealer centrality premium and competition between dealers in the dealer-customer market generates a centrality discount.

2.A.1 Network Structure and Timing

We focus on a star network where a single (core) dealer is connected with $N \geq 2$ (peripheral) dealers. The total number of dealers is therefore $N+1$ and we refer to the core dealer as dealer 0. Peripheral dealers cannot trade directly with each other so all interdealer trades go through the core dealer. There is one risk-free asset with zero interest rate and one risky asset with payoff $\tilde{v} \sim N(\bar{v}, \sigma^2)$. Dealers are risk averse and have exponential utility with risk-aversion coefficient γ. Dealer $i \in \{0, 1, ..., N\}$ has an initial endowment of w_i units of the risk-free asset and x_i units of the risky asset. Each dealer trades strategically by taking into account all other dealers' optimal trading strategies. The model has three dates:

- **Date 0: Bidding game.** The customer submits an order for z units of the risky asset where $z > 0$ denotes a customer sell order (the dealer buys) and $z < 0$ is a customer buy order (the dealer sells). Dealers compete on offering the best price to win the customer order. In case multiple dealers offer the same best price then the customer randomly selects one of these dealers to trade with.

- **Date 1: Network trading game.** Dealers trade simultaneously with all directly connected trading partners in the interdealer network to distribute and smooth their inventories due to risk aversion.

- **Date 2: Payoffs.** The payoff of the risky asset $\tilde{v}$ is realized and agents are paid off.

Huang and Wei (2017) solve the model for the subgame perfect Nash equilibrium using backward induction starting on date 1.

2.A.2 Network Trading Game Equilibrium

To derive the linear equilibrium in the interdealer market, Huang and Wei (2017) follows Kyle (1989), Vives (2011), and Babus and Kondor (2018) in assuming exogenous liquidity supply. This assumption is required for the existence of a linear equilibrium and can be interpreted as outside arbitrageurs trading against the dealers when prices are attractive. In particular, for each bilateral interdealer connection there is a downward sloping liquidity supply $\beta(p_i - \bar{v})$ where $\beta < 0$ and p_i is the interdealer price between the core dealer and peripheral dealer i. This exogenous liquidity supply can be interpreted as limited arbitrage: risk-neutral arbitrageurs buy the risky asset when $p_i < \bar{v}$, sell when $p_i > \bar{v}$, and the maximum number of units they can trade is proportional to $p_i - \bar{v}$.

At date 1 before interdealer trading begins, dealer i owns w_i' units of the risk-free asset and x_i' of the risky asset. If dealer i won the customer's order at date 0 then she has $w_i' = w_i - P^* z$ and $x_i' = x_i + z$ where P^* is the winning price in the customer transaction on date 0. In each interdealer connection, the core dealer buys or sells Q_i units of the risky asset while peripheral dealer i buys or sells q_i units. Excess demand from this interdealer connection is absorbed by the exogenous liquidity supply. The market clearing condition is therefore $Q_i + q_i + \beta(p_i - \bar{v}) = 0$. Proposition 5 in Huang and Wei (2017) shows that the equilibrium interdealer prices and quantities between the core dealer and each peripheral dealer $i \in \{1, \ldots, N\}$ are

$$\begin{aligned} p_i &= \bar{v} - \frac{\gamma\sigma^2}{2}\left(\frac{c}{c+\beta}x_i' + \theta X'\right) \\ Q_i &= -\frac{\gamma\sigma^2(c+\beta)}{2}\left(\frac{c}{c+\beta}x_i' - \theta X'\right) \\ q_i &= \frac{\gamma\sigma^2 c}{2}\left(\frac{c+2\beta}{c+\beta}x_i' - \theta X'\right) \end{aligned} \tag{A1}$$

where

$$\begin{aligned} X' &\equiv x_0' - \frac{b}{2}\sum_{i=1}^{N} x_i' \\ \theta &\equiv \frac{2}{2 - N\gamma\sigma^2(c+\beta)} \\ b &\equiv \gamma\sigma^2 c \end{aligned}$$

Proposition 3 in Huang and Wei (2017) states that there is a unique linear equilibrium where $c \in \left(-\frac{1}{\gamma\sigma^2}, 0\right)$ is part of the solution. One can interpret the coefficient c as the core dealer's willingness to share and distribute the peripheral dealers' inventories. The core dealer is less willing to perform inventory risk sharing (c is closer to zero) when the exogenous liquidity supply is low, dealers are more risk averse, and when the asset is more risky. From equation (A1) it is clear that $\frac{\partial Q_i}{\partial x_i'} > 0$ and that $\frac{\partial q_i}{\partial x_i'} < 0$ because $c < 0$ and $\beta < 0$. These signed derivatives reflect the core dealer's role of performing inventory risk sharing in the interdealer network. The core dealer buys more from peripheral dealer i when this peripheral dealer has a greater demand for selling inventory.

Interdealer centrality premium

To analyze how interdealer prices vary, we sort peripheral dealers increasingly by their date 1 inventories

$$x_1' < x_2' < \cdots < x_s' < x_{s+1}' < \cdots < x_N'$$

where the inventories of peripheral dealers s and $s+1$ are such that $q_s > 0$ and $q_{s+1} < 0$. Peripheral dealers $i \in \{s+1, \ldots, N\}$ with high inventory levels sell to the core dealer. In turn, the core dealer sells to peripheral dealers $i \in \{1, \ldots, s\}$ and thereby performs inventory risk sharing throughout the interdealer network. We determine the sign of the interdealer centrality spread by comparing buy and sell prices between the core and peripheral dealers respectively. Because the interdealer price p_i from equation (A1) decreases with x_i' we have that $p_s > p_{s+1}$.

The ordering of peripheral dealers' inventories implies that the core dealer sells to peripheral dealers at prices of at least p_s. When peripheral dealers sell to the core dealer they do so at prices of at most p_{s+1}. The fact that $p_s > p_{s+1}$ shows that the core dealer sells at higher prices than peripheral dealers do in the interdealer market. Since each transaction involves both a buyer and a seller, it is also clear that the core dealer buys at lower interdealer prices than peripheral dealers do. The model therefore has an interdealer centrality premium because of dealer market power originating from bilateral trading in the network. Since the core dealer has a connection advantage in the interdealer market, she trades at more favorable interdealer prices than peripheral dealers do.

2.A.3 Bidding Game Equilibrium

The bidding game at date 0 has two possible equilibria: either the core dealer or one of the peripheral dealers wins the customer's order. We assume the customer submits a sell order (i.e., $z > 0$) to reflect the trading direction of index trackers at exclusion. The case of a buy order can be analyzed in the same way with the maximum bid price replaced by the minimum ask price. Huang and Wei (2017) use reservation prices Ψ_{ij} associated with dealer j ($j \neq i$) winning the customer order to characterize the bidding game equilibrium. Conditional on dealer j winning the customer's order then Ψ_{ij} is the maximum bid price that dealer i is willing to pay in order to outbid dealer j and thereby win the customer's order. In particular, Ψ_{ij} is defined from dealer i's utility function u_i

$$u_i(w_i - \Psi_{ij} z, \boldsymbol{x} + z\boldsymbol{e}_i) = u_i(w_i, \boldsymbol{x} + z\boldsymbol{e}_j)$$

where $\boldsymbol{x} \equiv (x_0, \ldots, x_N)^T$ is a vector of initial inventories and $\boldsymbol{e}_k$ is an $N+1$-dimensional vector of zeros except for the k^{th} element which is equal to one. Proposition 6 in Huang and Wei (2017) shows that the reservation prices are given by

$$\begin{aligned}
\Psi_{0i} &= \bar{v} + \psi_z z + \psi_x x_i + \psi_X X \\
\Psi_{i0} &= \bar{v} + \psi_z' z + \psi_x' x_i + \psi_X' X \\
\Psi_{ij} &= \bar{v} + \psi_z'' z + \psi_x'' x_i + \psi_X'' X
\end{aligned} \tag{A2}$$

where $X \equiv x_0 - \frac{b}{2}\sum_{i=1}^{N} x_i$ and the coefficients are

$$\psi_z = \frac{1}{2}\psi_x + \frac{1}{2}\left(1 - \frac{b}{2}\psi_X\right)$$
$$\psi_x = \frac{b^2}{2(c+\beta)}$$
$$\psi_X = -\frac{1}{2}\gamma\sigma^2\theta(2+b)$$

and

$$\psi'_z = \frac{1}{2}\psi'_x + \frac{1}{2}\left(1 - \frac{b}{2}\psi'_X\right)$$
$$\psi'_x = \left[-\gamma\sigma^2 - \frac{\gamma\sigma^2}{4}b(2+b)\left(\frac{c+2\beta}{c+\beta} + \left(1+\frac{b}{2}\right)\theta\right)\frac{c+2\beta}{c+\beta}\right]$$
$$\psi'_X = \left[\frac{\gamma\sigma^2}{4}b(2+b)\left(\frac{c+2\beta}{c+\beta} + \left(1+\frac{b}{2}\right)\theta\right)\theta\right]$$

and

$$\psi''_z = \frac{1}{2}\psi''_x - \frac{1}{2}b\psi''_X$$
$$\psi''_x = -\gamma\sigma^2 - \frac{\gamma\sigma^2}{4}b(2+b)\left(\frac{c+2\beta}{c+\beta}\right)^2$$
$$\psi''_X = \frac{\gamma\sigma^2}{4}b(2+b)\frac{c+2\beta}{c+\beta}\theta$$

All these coefficients $\psi_z, \psi'_z, \psi''_z, \psi_x, \psi'_x, \psi''_x, \psi_X, \psi'_X, \psi''_X$ are negative. This feature implies that the reservation prices can be ranked based on peripheral dealers' inventories.

Trading with core versus peripheral dealers

Huang and Wei (2017) use the ranking of reservation prices to determine the bidding game equilibrium in their Proposition 7: when sorting peripheral dealers increasingly by their initial inventories x_i, the core dealer wins the customer's sell order if and only if

$$x_0 \leq \frac{\psi_z - \psi'_z}{\psi'_X - \psi_X}z + \frac{\psi_x - \psi'_x}{\psi'_X - \psi_X}x_1 + \frac{b}{2}\sum_{i=1}^{N} x_i \tag{A3}$$

This condition highlights the key trade-off in the model. The core dealer has a comparative advantage in inventory management because she can trade directly with all peripheral dealers. For a given order size z, this connection advantage implies that the core dealer wins the customer's sell order as long as her inventory is not too much higher than peripheral inventories. As the core dealer's inventory level increases, it will eventually outweigh the connection advantage and allow a peripheral dealer to win the customer's order. Huang and Wei (2017) also show that the fractions multiplying the order size z and initial inventory x_1 in equation (A3) are non-negative. This feature implies that peripheral dealers are less likely to win the customer order when the trade size is large and when their initial inventories are large. The reason is that in both cases, peripheral dealers need to trade larger amounts with the core dealer in the interdealer market to share inventory risk and therefore have a lower incentive to win the customer order.

Customer-dealer centrality discount

We derive the centrality spread in the customer-dealer market by comparing prices from the two possible outcomes that either the core or a peripheral dealer wins the customer order. The condition in equation (A3) implies that the equilibrium dealer-customer price P^* is a piece-wise linear function of $X \equiv x_0 - \frac{b}{2}\sum_{i=1}^{N} x_i$

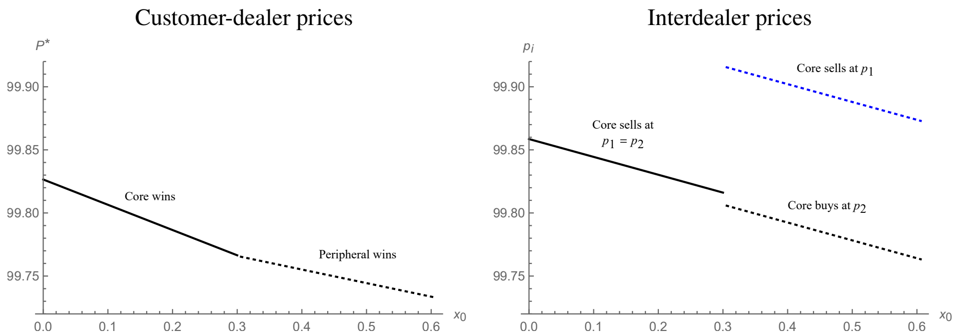
$$P^*(X) = \begin{cases} \Psi_{0i} = \bar{v} + \psi_z z + \psi_x x_i + \psi_X X, & \text{when } X \leq \dfrac{\psi_z - \psi'_z}{\psi'_X - \psi_X} z + \dfrac{\psi_x - \psi'_x}{\psi'_X - \psi_X} x_1 \\ \Psi_{i0} = \bar{v} + \psi'_z z + \psi'_x x_i + \psi'_X X, & \text{when } X > \dfrac{\psi_z - \psi'_z}{\psi'_X - \psi_X} z + \dfrac{\psi_x - \psi'_x}{\psi'_X - \psi_X} x_1 \end{cases} \tag{A4}$$

The difference between the two reservation prices $\Psi_{0i} - \Psi_{i0}$ is zero when $X = \frac{\psi_z - \psi'_z}{\psi'_X - \psi_X} z + \frac{\psi_x - \psi'_x}{\psi'_X - \psi_X} x_1$, so $P^*(X)$ is a continuous function of X. The equilibrium dealer-customer price decreases with X because $\psi_X < 0$ and $\psi'_X < 0$. When the core dealer wins the customer's sell order, she therefore buys at a higher price $P^*(X) = \Psi_{0i}$ than when a peripheral dealer wins the order and $P^*(X) = \Psi_{i0}$. The model therefore has a customer-dealer centrality discount because dealers compete for the customer order. The core dealer's connection advantage in the interdealer market implies that the customer receives a better price when the core dealer wins the order.

2.A.4 Numerical example

To illustrate the features of the model, we consider a customer sell order $z = 1$ and set $N = 2$, $\bar{v}$=100, $\sigma = 0.25$, $\gamma = 10$, $\beta = -1$. We assume peripheral initial inventories are zero $x_1 = x_2 = 0$. Equation (A3) specifies that the core dealer wins the customer's sell order when $x_0 \leq 0.31$. In this case, the core dealer subsequently sells part of the order to the peripheral dealers in the interdealer market. When $x_0 > 0.31$, the two peripheral dealers post the same bid price and the customer randomly trades with one of them. Assuming peripheral dealer 2 wins the customer's order, she then sells part of the order at price p_2 to the core dealer who in turn sells to peripheral dealer 1 at price p_1. The figures below show the equilibrium customer-dealer and interdealer prices as a function of the initial core inventory x_0.

The solid (dashed) line denotes the equilibrium in which the core (peripheral) dealer wins the customer's order. The figure on the left shows that the core dealer buys at higher prices from the customer than peripheral dealers do. This result implies a customer-dealer centrality discount. The figure on the right shows interdealer prices. When the core dealer wins the customer order, she sells part of it to each of the peripheral dealers at the same price $p_1 = p_2$. The prices are



identical because peripheral inventories are the same $x_1' = x_2' = 0$. When peripheral dealer 2 wins the customer order, the peripheral inventories are $x_2' = z > 0$ and $x_1' = 0$. This difference in inventories implies that $p_1 > p_2$. The price at which peripheral dealer 2 sells to the core dealer (dashed black line) is below the price at which the core dealer sells to (1) peripheral dealer 1 in the same equilibrium (dashed blue line) and (2) both peripheral dealers in the other equilibrium (solid black line). The core dealer therefore sells at higher interdealer prices than peripheral dealers do. Conversely, the same figure shows that the core dealer buys at lower interdealer prices than peripheral dealers do. These results imply an interdealer centrality premium.

2.B Affiliate Trades

When FINRA-registered dealers transfer bonds to their non-FINRA affiliates for bookkeeping purposes, the trades are registered in TRACE as customer–dealer trades before November 2015. Affiliate trades are not actual risk transfers between dealers and customers and should therefore be deleted (see e.g., Adrian et al. (2017), Bessembinder et al. (2018), Choi et al. (2022), and An (2020)). We use a filter to identify and delete affiliate trades before November 2015. Specifically, we identify two offsetting trades by the same dealer in the same bond with the same volume and the same price executed within 60 seconds of each other where at least one counterparty is a customer. Because the dealer buys and sells at the same price, all these paired trades have zero spread. We infer that the customer trade is likely an affiliate trade because the dealer would normally be compensated for finding a counterparty. For each dealer in each year, we divide the volume of zero-spread paired trades when both counterparties are customers by the same number plus the volume of non-zero-spread paired trades involving at least one customer. We then delete the customer trade(s) in zero-spread paired trades by those dealers with a ratio greater than 25%. We confirm that our filter has a high matching accuracy using actual counterparty information from November 2015 to September 2018.

2.C Additional Tables

Table A1: Speed of inventory adjustment (degree centrality)

Panel A presents coefficient estimates from the regression:

$$\beta_{im} = \alpha + \theta Centrality_{im} + \delta_m + \epsilon_{im}$$

where β_{im} is the estimated speed of inventory adjustment for dealer i in month m. $Centrality_{im}$ is the degree centrality score based on all interdealer transactions during the month. The second and fourth column include month fixed effects δ_m. For each month, we estimate the speed of inventory adjustment for every dealer with a non-negative cumulative inventory buildup of excluded bonds over event days -3 to 0 using the regression:

$$I_t - I_{t-1} = \beta(I_{t-1} - \alpha_0 - \alpha_1 I_{[t>=20]})$$

where I_t is the cumulative inventory across all excluded bonds for a given dealer on event day t, α_0 represents the target level of inventory before the exclusion event $[t \in \{-50, \cdots, -20\}]$, and α_1 represents the change in target level of inventory after the exclusion event $[t \in \{20, \cdots, 100\}]$. Event day 0 is the exclusion date. The t-statistics are reported in parenthesis with the convention *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. Panel B shows the average inventory half-life for dealer quartiles based on degree centrality scores. The half-life quantity is obtained using the formula $-\ln(2)/\ln(1+\bar{\beta})$.

Panel A: Inventory adjustment speed

	Maturity exclusions		Downgrade exclusions	
Centrality	-0.0002***	-0.0001***	-0.0001***	-0.0001***
	(-13.29)	(-11.25)	(-5.48)	(-4.45)
Constant	-0.10***		-0.09***	
	(-36.79)		(-23.00)	
Month FE	No	Yes	No	Yes
Adj. R^2	0.02	0.03	0.01	0.03
Months	193	193	151	148
Observations	10,449	10,449	4,144	4,141

Panel B: Inventory half-life

Quartile	Mean	Median	Mean	Median
1 Low centrality	8.31	22.76	8.31	22.76
2	4.60	11.20	5.42	13.51
3	4.27	8.31	4.98	11.20
4 High centrality	4.60	7.35	5.95	9.55

Table A2: Centrality spread for customer-dealer trades (degree centrality)

This table presents coefficient estimates from the regression:

$$Price_{ijt} = \beta Centrality_{it} + \gamma Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

where $Price_{ijt}$ is the volume-weighted dealer buy or sell price measured in basis points for dealer i, bond j, and day t. All prices are from the dealer's perspective. For index exclusions, we calculate the dealer buy price over event days -3 to 0 where event day 0 is the exclusion date. We compute the dealer sell price on each event day $t \in \{1, \ldots, 30\}$ after the exclusion date. In the sample of all corporate bonds, we compute dealer-bond specific volume-weighted buy and sell prices on each trading day. $Centrality_{it}$ is the degree centrality based on all inter-dealer transactions during the exclusion month. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. $Volume_{ijt}$ is the cumulative volume of the transactions used to compute the volume-weighted dealer-bond specific price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to August 2018. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions		All corporate bonds	
	Buy from customer	Sell to customer	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Centrality	0.008***	-0.016***	0.085	-0.061***	0.024***	-0.043***
	(5.09)	(-13.41)	(1.06)	(-7.98)	(21.40)	(-30.74)
Log(Volume)	2.592***	-2.537***	9.474***	-19.922***	5.105***	-9.994***
	(14.20)	(-14.83)	(2.97)	(-10.90)	(17.55)	(-29.37)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.995	0.992	0.984	0.993	0.998	0.997
Issuers (clusters)	1056	970	336	350	4,475	4,548
Days (clusters)	194	3,690	145	1,954	4,064	4,078
Bonds	4,346	4,065	944	947	26,675	29,331
Observations	17,156	52,997	5,076	24,615	4,226,371	5,617,312

Table A3: Centrality spread for interdealer trades (degree centrality)

This table presents coefficient estimates from the regression:

$$Price_{jt} = \beta_1 Buyer\ centrality_t + \beta_2 Seller\ centrality_t + \gamma Log(Volume_{jt}) + \delta_{jt} + \epsilon_{jt}$$

where $Price_{jt}$ is the volume-weighted interdealer price measured in basis points between the buying and selling dealer for bond j on day t. For index exclusions, we calculate the interdealer price on each event day $t \in \{-3, ..., 30\}$ where event day 0 is the exclusion date. In the sample of all corporate bonds, we compute interdealer prices on each trading day. $Buyer\ centrality_t$ and $Seller\ centrality_t$ denote the degree centrality scores of the buying and selling dealer based on all interdealer transactions during the exclusion month. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. $Volume_{jt}$ is the cumulative volume of the transactions used to compute the volume-weighted price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to August 2018. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions	Downgrade exclusions	All corporate bonds
Buyer centrality	-0.011***	-0.024***	-0.011***
	(-8.83)	(-3.11)	(-12.54)
Seller centrality	0.016***	0.023***	0.013***
	(10.83)	(4.55)	(16.90)
Log(Volume)	-1.085***	0.445	-2.023***
	(-3.87)	(0.24)	(-12.77)
Bond×day FE	Yes	Yes	Yes
Adj. R^2	0.995	0.997	0.998
Issuers (clusters)	1,079	372	4,808
Days (clusters)	3,844	2,594	4,065
Bonds	4,400	1,078	35,603
Observations	80,622	69,485	9,815,924

Table A4: Centrality spread for prearranged trades (degree centrality)

This table presents coefficient estimates from the regression:

$$Markup_{ijt} = \beta Centrality_{it} + \gamma Log(Trade\ size_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

where $Markup_{ijt}$ is measured in basis points for the prearranging dealer i, bond j on day t. $Centrality_{it}$ is the degree centrality score based on all interdealer transactions during the exclusion month for each dealer in the prearranged trade. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. For index exclusions, we use prearranged trades on event days -3 to 0 where event day 0 is the exclusion date. In the sample of all corporate bonds, we use prearranged trades on all trading days. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to August 2018. We cluster standard errors by bond issuer and month for index exclusions and by bond issuer and trading day in the sample of all corporate bonds. We report t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	CDC			DDD		
	Maturity	Downgrade	All bonds	Maturity	Downgrade	All bonds
Seller centrality				-0.001	-0.008	0.001**
				(-0.30)	(-1.38)	(2.57)
Prearranging centrality	0.008	-0.073	0.000	-0.009***	-0.021**	-0.015***
	(0.77)	(-1.42)	(0.03)	(-3.64)	(-2.52)	(-13.66)
Buyer centrality				0.467	1.576	0.720**
				(0.72)	(0.59)	(2.49)
Log(Volume)	-0.157	-4.074	-0.966**	-0.808**	-1.065	0.082
	(-1.19)	(-0.41)	(-2.55)	(-2.08)	(-1.52)	(0.78)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.707	0.300	0.638	0.299	0.512	0.447
Issuers (clusters)	131	85	3,253	119	93	3,109
Months/days (clusters)	153	136	3,979	215	174	4,039
Bonds	148	132	10,354	211	188	15,372
Observations	352	411	80,176	551	850	432,926

	CDD			DDC		
	Maturity	Downgrade	All bonds	Maturity	Downgrade	All bonds
Seller centrality				0.018***	0.035	0.029***
				(4.12)	(1.15)	(11.86)
Prearranging centrality	-0.024***	-0.091***	-0.047***	-0.011**	-0.035	-0.047***
	(-3.03)	(-5.01)	(-17.01)	(-2.51)	(-0.64)	(-13.63)
Buyer centrality	-0.003	0.022	0.007***			
	(-0.42)	(0.82)	(4.54)			
Log(Volume)	-0.617**	-3.247	-5.476***	-2.134***	-16.860***	-11.282***
	(-2.37)	(-0.87)	(-9.66)	(-5.72)	(-3.18)	(-16.25)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.453	0.166	0.478	0.325	0.287	0.548
Issuers (clusters)	199	53	2,150	339	90	2,886
Months/days (clusters)	82	45	3,882	144	64	4,040
Bonds	295	95	9,067	700	178	16,058
Observations	813	300	96,390	2,234	769	417,355

Table A5: Network centrality by subperiod (degree centrality)

Panel A presents coefficient estimates from the time-series regression:

$$VW\ centrality_m = \beta_0 + \beta_1 Crisis_m + \beta_2 Post\text{-}crisis_m + \beta_3 Volcker_m + \epsilon_{im}$$

where $VW\ centrality_m$ is the volume-weigthed average degree centrality score in month m. We compute the centrality score for each dealer based on all interdealer transactions during the exclusion month. For index exclusions, we weigh centrality scores by the buy volume from customers over event days [-3, 0] where event day 0 is the exclusion date. In the sample of all corporate bonds, we weigh centrality scores by the buy volume from customers over the entire month. We use the pre-crisis period from July 2002 to June 2007 from as the omitted group and include indicator variables for the crisis period from July 2007 to December 2009, the post-crisis period from January 2010 to June 2014, and the Volcker period from July 2014 to August 2018. We use robust standard errors and report t-statistics in parenthesis. Panel B presents coefficient estimates from the panel regression:

$$Centrality_{im} = \beta_0 + \beta_1 Crisis_m + \beta_2 Post\text{-}crisis_m + \beta_3 Volcker_m + \delta_i + \epsilon_{im}$$

where $Centrality_{im}$ is the degree centrality score for dealer i in month m. We use the pre-crisis period as the omitted group and include indicator variables for the remaining time periods together with dealer fixed effects δ_i. For index exclusions, we consider dealers that buy from customers on event days -3 to 0 only. Standard errors are clustered by dealer and month with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions	Downgrade exclusions	All corporate bonds
Panel A: Volume-weighted network centrality			
Pre-crisis (β_0)	197.339***	202.028***	192.092***
	(52.97)	(31.45)	(88.20)
Crisis	52.859***	16.082	29.313***
	(4.37)	(0.93)	(5.96)
Post-crisis	115.916***	71.039***	104.965***
	(20.25)	(5.75)	(31.30)
Volcker	133.517***	102.568***	120.751***
	(24.26)	(7.39)	(41.87)
Adj. R^2	0.698	0.293	0.884
Observations	194	156	194
Panel B: Within-dealer variation in centrality			
Pre-crisis (β_0)	152.939***	145.911***	21.668***
	(15.98)	(14.59)	(25.77)
Crisis	25.988***	26.611**	3.150**
	(2.70)	(2.60)	(2.39)
Post-crisis	67.312***	72.352***	11.842***
	(5.00)	(4.61)	(8.23)
Volcker	63.896***	71.689***	11.765***
	(3.88)	(3.95)	(6.74)
Dealer FE	Yes	Yes	Yes
Adj. R^2	0.857	0.884	0.854
Months (clusters)	194	156	194
Observations	8,730	3,539	198,044

Table A6: Centrality spread by subperiod (degree centrality)

Panel A presents coefficient estimates for customer–dealer trades from the regression:

$$Price_{ijt} = \sum_s \beta_s Centrality_{it} \mathbb{1}_s + \gamma Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

and Panel B presents coefficient estimates for interdealer trades from the regression:

$$Price_{jt} = \sum_s \beta_s Buyer\ centrality_t \mathbb{1}_s + \sum_s \eta_s Seller\ centrality_t \mathbb{1}_s + \gamma Log(Volume_{jt}) + \delta_{jt} + \epsilon_{jt}$$

where $\mathbb{1}_s$ is an indicator variable that takes a value of 1 in subperiod s. We use four subperiods: pre-crisis is from July 2002 to June 2007, crisis is from July 2007 to December 2009, post-crisis is from January 2010 to June 2014, and the Volcker period is from July 2014 to August 2018. The remaining variables are defined in Table 7 for customer–dealer trades and Table 8 for interdealer trades. We do not report coefficient estimates on $Log(Volume_{jt})$. All regressions include bond-times-day fixed effects δ_{jt}. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions		All corporate bonds	
Panel A: Centrality spread for customer–dealer trades						
	Buy from customer	Sell to customer	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Pre-crisis	0.011***	-0.029***	0.089*	-0.076***	0.030***	-0.055***
	(2.76)	(-11.84)	(1.90)	(-4.97)	(11.42)	(-14.01)
Crisis	0.017**	-0.027***	0.192	-0.060	0.025***	-0.054***
	(2.32)	(-5.00)	(0.78)	(-1.23)	(9.72)	(-17.26)
Post-crisis	0.012***	-0.012***	0.078**	-0.043**	0.026***	-0.042***
	(3.34)	(-5.33)	(2.37)	(-2.34)	(13.85)	(-15.40)
Volcker	0.001	-0.010***	-0.020	-0.062***	0.017***	-0.031***
	(0.71)	(-7.65)	(-1.38)	(-6.32)	(15.27)	(-19.77)
Adj. R^2	0.995	0.992	0.984	0.993	0.998	0.997
Observations	17,156	52,997	5,076	24,615	4,226,371	5,617,312
t-test (Post<Pre)	0.17	5.05***	-0.21	1.38	-1.22	2.40**
t-test (Volcker<Pre)	-2.29**	6.29***	-2.42**	0.71	-4.19***	5.30***
Panel B: Centrality spread for interdealer trades						
	Buyer centrality	Seller centrality	Buyer centrality	Seller centrality	Buyer centrality	Seller centrality
Pre-crisis	-0.011***	0.008***	-0.054***	0.038***	-0.018***	0.013***
	(-2.63)	(2.94)	(-4.17)	(5.31)	(-6.18)	(6.34)
Crisis	-0.029***	0.040***	-0.073	0.019	-0.029***	0.043***
	(-8.47)	(6.52)	(-1.29)	(0.84)	(-12.07)	(17.20)
Post-crisis	-0.005***	0.011***	-0.007	0.010***	-0.006***	0.007***
	(-3.64)	(4.58)	(-1.54)	(2.78)	(-9.07)	(12.98)
Volcker	-0.005***	0.007***	-0.003	0.024***	-0.005***	0.007***
	(-10.20)	(9.13)	(-0.92)	(5.25)	(-9.61)	(15.14)
Adj. R^2	0.995		0.997		0.998	
Observations	80,622		69,485		9,815,924	
t-test (Post<Pre)	1.39	0.83	3.58***	-3.73***	4.15***	2.79***
t-test (Volcker<Pre)	1.41	-0.43	3.98***	-1.72*	4.42***	-2.91***

Table A7: Trade size and dealer centrality (degree centrality)

This table presents coefficient estimates from the regression:

$$Log(Trade\ size_{ijt}) = \sum_s \beta_s Centrality_{it} \mathbb{1}_s + \delta_{jt} + \epsilon_{ijt}$$

where $Trade\ size_{ijt}$ is for dealer i, bond j, and day t. For index exclusions, we use transactions on event days -3 to 0 where event day 0 is the exclusion date. $Centrality_{it}$ is the degree centrality score based on all interdealer transactions during the exclusion month. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. $\mathbb{1}_s$ is an indicator variable that takes a value of one in time period s. We use four time periods: the pre-crisis period is from July 2002 to June 2007, the crisis period is from July 2007 to December 2009, the post-crisis period is from January 2010 to June 2014, and the Volcker period is from July 2014 to August 2018. All regressions include bond-times-day fixed effects δ_{jt}. We exclude trade sizes below $\$100,000$. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions		All corporate bonds	
	Buy from customer	Sell to customer	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Centrality*Pre-crisis	-0.002***	-0.001***	0.000	0.001***	-0.001***	-0.001***
	(-8.55)	(-7.70)	(0.18)	(2.90)	(-7.90)	(-7.76)
Centrality*Crisis	0.000	0.000	-0.001	0.001	-0.000	0.000***
	(0.21)	(0.53)	(-1.37)	(1.32)	(-1.62)	(2.68)
Centrality*Post-crisis	0.001***	0.000**	0.001***	0.001***	0.001***	0.001***
	(3.08)	(1.97)	(2.69)	(5.36)	(12.06)	(12.96)
Centrality*Volcker	0.002***	0.001***	0.002***	0.001***	0.001***	0.001***
	(7.53)	(11.19)	(4.96)	(5.50)	(14.61)	(15.83)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	-0.028	0.230	0.110	0.375	0.249	0.283
Issuers (clusters)	1,091	966	357	349	4,598	4,662
Days (clusters)	768	3,690	522	1,954	4,067	4,082
Observations	30,561	63,169	12,014	31,827	5,413,629	7,141,579

Table A8: Centrality spread for customer–dealer trades (all trade sizes)

This table presents coefficient estimates from the regression:

$$Price_{ijt} = \beta Centrality_{it} + \gamma Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

where $Price_{ijt}$ is the volume-weighted dealer buy or sell price measured in basis points for dealer i, bond j, and day t. All prices are from the dealer's perspective. For index exclusions, we calculate the dealer buy price over event days -3 to 0 where event day 0 is the exclusion date. We compute the dealer sell price on each event day $t \in \{1, \ldots, 30\}$ after the exclusion date. In the sample of all corporate bonds, we compute dealer-bond specific volume-weighted buy and sell prices on each trading day. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. $Volume_{ijt}$ is the cumulative volume of the transactions used to compute the volume-weighted dealer-bond specific price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to August 2018. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions		All corporate bonds	
	Buy from customer	Sell to customer	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Centrality	17.020***	-6.343***	30.519	-16.052***	30.033***	-13.595***
	(9.82)	(-8.08)	(1.59)	(-3.74)	(39.12)	(-15.45)
Log(Volume)	6.253***	-1.629***	16.538***	-16.129***	10.092***	-11.427***
	(18.44)	(-15.32)	(6.44)	(-15.32)	(26.79)	(-46.87)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.977	0.983	0.984	0.992	0.996	0.993
Issuers (clusters)	1,102	1,120	359	384	4,674	4,737
Days (clusters)	194	3,995	147	2,691	4,084	4,091
Bonds	4,652	4,737	1,010	1,067	31,176	34,713
Observations	24,440	143,789	7,853	74,415	13,873,675	17,834,852

Table A9: Centrality spread for interdealer trades (all trade sizes)

This table presents coefficient estimates from the regression:

$$Price_{jt} = \beta_1 Buyer\ centrality_t + \beta_2 Seller\ centrality_t + \gamma Log(Volume_{jt}) + \delta_{jt} + \epsilon_{jt}$$

where $Price_{jt}$ is the volume-weighted interdealer price measured in basis points between the buying and selling dealer for bond j on day t. For index exclusions, we calculate the interdealer price on each event day $t \in \{-3, \ldots, 30\}$ where event day 0 is the exclusion date. In the sample of all corporate bonds, we compute interdealer prices on each trading day. $Buyer\ centrality_t$ and $Seller\ centrality_t$ denote the eigenvector centrality scores of the buying and selling dealer based on all interdealer transactions during the exclusion month. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. $Volume_{jt}$ is the cumulative volume of the transactions used to compute the volume-weighted price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to August 2018. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions	Downgrade exclusions	All corporate bonds
Buyer centrality	-5.727***	-13.778***	-7.027***
	(-9.96)	(-2.97)	(-13.60)
Seller centrality	9.622***	14.396***	6.998***
	(10.00)	(4.52)	(15.64)
Log(Volume)	-1.081***	0.467	-2.062***
	(-3.89)	(0.25)	(-13.00)
Bond×day FE	Yes	Yes	Yes
Adj. R^2	0.995	0.997	0.998
Issuers (clusters)	1,079	372	4,808
Days (clusters)	3,844	2,594	4,065
Bonds	4,400	1,078	35,603
Observations	80,622	69,485	9,815,924

Table A10: Centrality spread for prearranged trades (all trade sizes)

This table presents coefficient estimates from the regression:

$$Markup_{ijt} = \beta Centrality_{it} + \gamma Log(Trade\ size_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

where $Markup_{ijt}$ is measured in basis points for the prearranging dealer i, bond j on day t. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month for each dealer in the prearranged trade. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. For index exclusions, we use prearranged trades on event days -3 to 0 where event day 0 is the exclusion date. In the sample of all corporate bonds, we use prearranged trades on all trading days. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to August 2018. We cluster standard errors by bond issuer and month for index exclusions and by bond issuer and trading day in the sample of all corporate bonds. We report t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	CDC			DDD		
	Maturity	Downgrade	All bonds	Maturity	Downgrade	All bonds
Seller centrality				-0.821	-0.261	0.095
				(-1.40)	(-0.15)	(0.83)
Prearranging centrality	4.697	-34.929	-5.780*	-9.930***	-22.296***	-13.030***
	(0.52)	(-1.16)	(-1.79)	(-7.43)	(-5.16)	(-21.15)
Buyer centrality				1.406***	-0.142	1.082***
				(2.96)	(-0.11)	(7.78)
Log(Volume)	-1.398***	-0.602	-5.405***	-0.227**	-0.250	-0.359***
	(-3.28)	(-0.15)	(-9.14)	(-2.09)	(-0.55)	(-8.55)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.537	0.222	0.644	0.367	0.386	0.356
Issuers (clusters)	171	101	3,553	439	176	3,884
Months/days (clusters)	204	175	4,048	593	337	4,051
Bonds	206	168	13,337	1,146	431	22,763
Observations	500	562	153,457	5,633	3,315	2,812,269

	CDD			DDC		
	Maturity	Downgrade	All bonds	Maturity	Downgrade	All bonds
Seller centrality				7.460***	11.507	17.846***
				(3.90)	(1.29)	(18.21)
Prearranging centrality	-7.211***	-15.620*	-9.912***	-16.599***	-46.244***	-33.800***
	(-3.72)	(-1.92)	(-11.42)	(-5.70)	(-4.07)	(-18.34)
Buyer centrality	1.316	19.062**	-1.548			
	(0.44)	(2.15)	(-1.48)			
Log(Volume)	-2.488***	-4.762***	-2.268***	-1.461***	-2.480	-2.405***
	(-11.30)	(-3.65)	(-9.24)	(-8.29)	(-1.21)	(-10.22)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.218	0.208	0.302	0.339	0.248	0.470
Issuers (clusters)	482	139	3,167	650	207	3,727
Months/days (clusters)	176	84	4,062	182	106	4,069
Bonds	1,398	398	19,586	1,967	528	26,467
Observations	5,573	3,387	2,752,891	13,048	6,455	7,249,781

Table A11: Centrality spread by subperiod (all trade sizes)

Panel A presents coefficient estimates for customer–dealer trades from the regression:

$$Price_{ijt} = \sum_s \beta_s Centrality_{it} \mathbb{1}_s + \gamma Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

and Panel B presents coefficient estimates for interdealer trades from the regression:

$$Price_{jt} = \sum_s \beta_s Buyer\ centrality_t \mathbb{1}_s + \sum_s \eta_s Seller\ centrality_t \mathbb{1}_s + \gamma Log(Volume_{jt}) + \delta_{jt} + \epsilon_{jt}$$

where $\mathbb{1}_s$ is an indicator variable that takes a value of 1 in subperiod s. We use four subperiods: pre-crisis is from July 2002 to June 2007, crisis is from July 2007 to December 2009, post-crisis is from January 2010 to June 2014, and the Volcker period is from July 2014 to August 2018. The remaining variables are defined in Table 5 for customer–dealer trades and Table 6 for interdealer trades. We do not report coefficient estimates on $Log(Volume_{jt})$. All regressions include bond-times-day fixed effects δ_{jt}. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions		All corporate bonds	
Panel A: Centrality spread for customer–dealer trades						
	Buy from customer	Sell to customer	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Pre-crisis	32.379***	-14.235***	47.145***	-45.534***	47.941***	-39.588***
	(5.19)	(-10.97)	(2.83)	(-6.24)	(35.38)	(-19.28)
Crisis	36.555***	-21.724***	62.203	-27.266*	42.268***	-24.154***
	(4.93)	(-6.40)	(0.74)	(-1.77)	(25.32)	(-15.45)
Post-crisis	19.970***	-1.261	18.481	14.791**	25.583***	-5.988***
	(10.42)	(-0.94)	(1.57)	(2.41)	(26.82)	(-4.21)
Volcker	-0.494	-0.727	3.135	-14.780***	21.684***	-6.826***
	(-0.30)	(-1.45)	(0.23)	(-2.89)	(28.76)	(-7.32)
Adj. R^2	0.977	0.983	0.984	0.992	0.996	0.993
Observations	24,440	143,789	7,853	74,415	13,873,675	17,834,852
t-test (Post<Pre)	-1.90*	6.54***	-1.61	6.29***	-13.21***	12.04***
t-test (Volcker<Pre)	-4.87***	9.63***	-2.52**	3.44***	-16.13***	14.07***

Panel B: Centrality spread for interdealer trades						
	Buyer centrality	Seller centrality	Buyer centrality	Seller centrality	Buyer centrality	Seller centrality
Pre-crisis	-9.731***	25.656***	-71.225***	54.126***	-32.930***	39.071***
	(-5.02)	(12.90)	(-11.20)	(7.63)	(-11.40)	(25.49)
Crisis	-29.499***	74.524***	-116.753***	130.766***	-61.188***	97.214***
	(-9.26)	(16.36)	(-4.08)	(3.82)	(-24.80)	(31.98)
Post-crisis	-4.889***	16.682***	-17.384***	27.313***	-15.305***	25.382***
	(-7.56)	(16.95)	(-7.62)	(7.56)	(-32.12)	(38.84)
Volcker	-6.056***	12.904***	-26.338***	33.743***	-18.767***	27.396***
	(-18.56)	(18.72)	(-12.77)	(8.89)	(-30.52)	(41.27)
Adj. R^2	0.985		0.997		0.997	
Observations	398,279		221,456		36,514,316	
t-test (Post<Pre)	2.50**	-4.13***	8.00***	-3.46***	5.97***	-8.61***
t-test (Volcker<Pre)	1.86*	-5.77***	6.74***	-2.59**	4.92***	-7.44***

Table A12: Trade size and dealer centrality (all trade sizes)

This table presents coefficient estimates from the regression:

$$Log(Trade\ size_{ijt}) = \sum_s \beta_s Centrality_{it} \mathbb{1}_s + \delta_{jt} + \epsilon_{ijt}$$

where $Trade\ size_{ijt}$ is for dealer i, bond j, and day t. For index exclusions, we use transactions on event days -3 to 0 where event day 0 is the exclusion date. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. $\mathbb{1}_s$ is an indicator variable that takes a value of one in time period s. We use four time periods: the pre-crisis period is from July 2002 to June 2007, the crisis period is from July 2007 to December 2009, the post-crisis period is from January 2010 to June 2014, and the Volcker period is from July 2014 to August 2018. All regressions include bond-times-day fixed effects δ_{jt}. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions		All corporate bonds	
	Buy from customer	Sell to customer	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Centrality*Pre-crisis	-0.532***	0.160	0.748***	0.172	-0.334***	-0.056
	(-3.51)	(1.52)	(2.79)	(1.22)	(-6.25)	(-1.37)
Centrality*Crisis	0.299	0.234***	0.782	1.038***	0.113**	0.321***
	(1.54)	(5.37)	(1.05)	(3.86)	(2.37)	(9.19)
Centrality*Post-crisis	0.985***	0.409***	1.343***	0.456***	0.312***	0.408***
	(9.03)	(5.48)	(6.58)	(3.30)	(8.81)	(13.22)
Centrality*Volcker	1.954***	1.415***	1.724***	0.835***	0.711***	0.861***
	(12.96)	(24.09)	(4.89)	(5.18)	(22.73)	(33.13)
Bond×day FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.130	0.341	0.310	0.387	0.372	0.393
Issuers (clusters)	1,131	1,115	377	383	4,780	4,839
Days (clusters)	775	3,995	556	2,691	4,086	4,093
Observations	47,738	217,386	23,652	143,143	18,593,734	29,243,552

Table A13: Centrality spread for customer–dealer trades (all dealers)

This table presents coefficient estimates from the regression:

$$Price_{ijt} = \beta Centrality_{it} + \gamma Log(Volume_{ijt}) + \delta_{jt} + \epsilon_{ijt}$$

where $Price_{ijt}$ is the volume-weighted dealer buy or sell price measured in basis points for dealer i, bond j, and day t. All prices are from the dealer's perspective. For index exclusions, we calculate the dealer buy price over event days -3 to 0 where event day 0 is the exclusion date. We compute the dealer sell price on each event day $t \in \{1, ..., 30\}$ after the exclusion date. In the sample of all corporate bonds, we compute dealer-bond specific volume-weighted buy and sell prices on each trading day. $Centrality_{it}$ is the eigenvector centrality score based on all interdealer transactions during the exclusion month. The centrality measure is therefore lagged by one month for index exclusions and we use the same lag in the sample of all corporate bonds. $Volume_{ijt}$ is the cumulative volume of the transactions used to compute the volume-weighted dealer-bond specific price. All regressions include bond-times-day fixed effects δ_{jt}. The sample period is from July 2002 to August 2018. Standard errors are clustered by bond issuer and trading day with t-statistics in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

	Maturity exclusions		Downgrade exclusions	
	Buy from customer	Sell to customer	Buy from customer	Sell to customer
Centrality	2.932***	-5.841***	16.264	-25.562***
	(3.30)	(-9.77)	(0.66)	(-6.63)
Log(Volume)	2.675***	-2.581***	10.740***	-20.090***
	(14.97)	(-14.82)	(4.21)	(-10.96)
Bond×day FE	Yes	Yes	Yes	Yes
Adj. R^2	0.994	0.992	0.985	0.993
Issuers (clusters)	1,095	970	357	350
Days (clusters)	194	3,690	147	1,954
Bonds	4,583	4,065	1,004	947
Observations	19,918	52,997	6,387	24,615

Chapter 3

Collateral Quality and Bidding Behavior in Central Bank Liquidity Auctions

Kjell G. Nyborg, University of Zurich

Obaidur Rehman, BI Norwegian Business School

Dagfinn Rime, BI Norwegian Business School

Olav Syrstad, BI Norwegian Business School, Norges Bank

Abstract

We examine the role of collateral quality for the bidding behavior of banks in central bank liquidity auctions. Using a novel dataset on banks' collateral pledging and bidding behavior, we show that banks exhibit strategic behavior in their collateral pledging decision. Specifically, banks pledge collateral with a lower outside option with the central bank. Moreover, we find that smaller banks with higher leverage and lower-quality collateral tend to draw disproportionally larger liquidity in central bank liquidity auctions. However, the price of liquidity is unrelated to the quality of pledged collateral. Our findings highlight the importance of the central bank collateral framework for liquidity provision.

3.1 Introduction

Collateral framework constitutes a fundamental pillar of central bank monetary policy. It dictates the terms under which banks can borrow in the central bank's secured liquidity operations. In the period following the great financial crisis, central banks have considerably increased the scale and scope of their liquidity facilities. At the same time, there has been a growing scarcity of high-quality collateral (Caballero et al., 2017).[1] Together, these developments have brought increasing attention to central bank collateral policy and its financial stability implications. Most recently, central banks across the globe expanded their collateral framework in response to the financial market meltdown of 2020 (European Central Bank, 2022).

On the one hand, collateral frameworks seek to be sufficiently broad to enable wide participation of financial intermediaries in central bank liquidity operations and to ensure smooth monetary policy transmission, particularly in times of crisis (Bindseil et al., 2017).[2] On the other hand, a collateral framework that is overly permissive may lead to risk transfers from the private sector to the central bank balance sheet and undermine market discipline (Nyborg, 2017).

There is now a growing body of empirical literature that documents the existence of the collateral channel of monetary policy (Van Bekkum et al., 2018; Fang et al., 2020; Mésonnier et al., 2022; Delatte et al., 2024; Hüttl and Kaldorf, 2024; Pelizzon et al., 2024). These studies examine the implications of changes in central bank collateral eligibility rules on asset prices and real economic outcomes. Most of these studies also acknowledge that easing collateral eligibility standards can potentially stimulate the overproduction of low-quality assets, which may contribute to financial fragility. Van Bekkum et al. (2018) show that a relaxation in the eligibility threshold of residential mortgage-backed securities by the European Central Bank (ECB) led to an expansion in credit supply to riskier borrowers. The authors argue that looser collateral requirements may lead to higher risk-taking and contribute to moral hazard. Pelizzon et al. (2024) provide evidence that the inclusion of a corporate bond in the ECB list of eligible collateral positively affects its secondary market liquidity and yield. The study emphasizes the role of collateral framework as an effective monetary policy tool for central banks.

In this study, we focus on examining the collateral pledging behavior of banks with Norges

[1] Caballero et al. (2017) document a secular decline in the availability of safe assets in the period following the great financial crisis. On the supply side of safe assets, Bechtel et al. (2021) shows that quantitative easing has contributed to a reduction in the availability and accessibility of safe assets in the Euro area. On the demand side of safe assets, Gorton et al. (2022) show that post-crisis bank regulations, such as the introduction of liquidity coverage ratio, have increased banks' demand for high-quality collateral. Moreover, Duffie et al. (2015) argues that increased demand for central clearing has added to the demand for safe collateral.

[2] Choi et al. (2021) show in a theoretical model that a broad collateral framework can contribute to market stability even during normal periods through its positive spillover effect on the composition of outstanding collateral in private markets. The authors, however, abstain from the ex-ante moral hazard introduced by lending against low-quality collateral.

Bank (NB), and how it relates to their bidding behavior in liquidity-providing auctions. NB regularly holds liquidity-injecting auctions as part of its normal market operations. The auctions follow an American-style arrangement and are usually held to counteract temporary deviations in the aggregate stock of banking reserves.

Banks face an opportunity cost when depositing collateral securities with the central bank, as these securities cannot be pledged elsewhere or traded. If the central bank collateral framework is generous, it is plausible that banks strategically pledge securities with the central bank with lower outside options. Moreover, as banks seek to economize the use of collateral, it is likely that banks pledging worse quality collateral display more aggressive bidding behavior in the auctions. In essence, banks have an incentive to adjust their bid prices upwards as long as the opportunity cost of the pledged collateral does not equilibrate with its outside option.

Norway provides a suitable laboratory to examine these effects. First, we obtain a very rich dataset on the composition of pledged and eligible collateral for all banks with an account with NB. This allows us to observe not only securities which banks pledge as collateral with NB but also those which they can potentially pledge from their eligible holdings stock. Hence, we can directly examine how the decision to pledge specific collateral security relates to its quality. Second, unlike the Eurosystem, banks in Norway are not subject to reserve requirements and, therefore, face a different set of constraints. As such, their decision to participate in the auctions reflects their individual liquidity needs.

We operationalize our analysis in two parts. Using proprietary bank-level data on the composition of pledged collateral and security holdings, we first examine the collateral pledging behavior of banks in Norway. To the best of our knowledge, this is the first paper to use such detailed bank-security-level data to study collateral pledging behavior.

If the central bank applies haircuts on collateral that does not adequately reflect market conditions, it would be optimal for banks to pledge relatively lower-quality collateral. Our results indeed show that banks are more likely to pledge relatively worse quality collateral with NB from within their eligible pool, presumably due to its lower opportunity cost compared to that of higher-quality collateral. The result complements the "haircut gap" notion documented in Jasova et al. (2023), wherein banks pledge more of those securities with the ECB with higher observable gaps in haircut values between the private market and the central bank.

Next, we examine how the quality of pledged collateral relates to the bidding behavior of banks in NB liquidity auctions. In a closely related study, Fecht et al. (2016) examines the bidding behavior of banks in Eurosystem repos. The authors show that banks in worse financial health and with lower-quality collateral exhibit disproportionally larger liquidity uptakes, which they interpret as suggestive evidence for systemic arbitrage.[3] Similarly, De Roure and McLaren (2021) analyzes banks' liquidity uptake in the Bank of England (BoE) uniform price liquidity auctions. They find that banks with lower-quality collateral tend to draw more liquidity. However,

[3]Drechsler et al. (2016) also show that weakly capitalized banks with riskier collateral borrow more in ECB liquidity operations.

they attribute this result to the design of the BoE collateral framework, which imposes a penalty fee on the use of lower-quality collateral in addition to the haircut adjustment. As a result, banks are incentivized to use the highest-quality collateral initially and turn to lower-quality collateral only when their demand for liquidity increases.

The richness of our dataset and the discriminatory setup of NB liquidity auctions allow us to study how collateral quality interacts with both the magnitude of banks' liquidity uptake and the price at which they acquire it while controlling for a wide range of other factors. Moreover, unlike Fecht et al. (2016), we focus on central bank liquidity provision and banks' pledging behavior under a period of relative normalcy.

We find that banks with worse quality collateral have larger liquidity uptakes in the auctions after controlling for their liquidity needs and financial health. This is consistent with banks maximizing the use of poor-quality collateral, which likely carries a higher haircut in private markets. The result suggests that by subsidizing haircuts on lower-quality collateral, the central bank may inadvertently incentivize banks to pledge more of it and borrow disproportionally larger amounts against it. However, we do not find that the price at which banks obtain liquidity in the auctions is related to the quality of their pledged collateral; instead, it is related to their individual and auction characteristics. This indicates that banks with lower-quality pledged collateral do not pay higher prices when borrowing in the central bank auctions.

The combination of larger liquidity uptakes against lower-quality collateral but not at higher prices supports the notion of systemic arbitrage laid out in Fecht et al. (2016). It also highlights that systemic arbitrage is not only present during a crisis but also during a period of economic stability. We would expect this if the central bank applies collateral haircuts that do not accurately reflect market conditions.

Furthermore, we find that the price of liquidity that a bank pays in an auction is independent of its distribution across the banking system. This contrasts with the finding of Fecht et al. (2011), which shows that bidding in Eurosystem repos is more aggressive when liquidity is more sparsely distributed among banks. The difference in results may stem from differences in the institutional design of the monetary system between the Euro area and Norway. The absence of reserve requirements in Norway implies that banks with surplus liquidity have limited incentives to hoard it as the excess liquidity is remunerated at a lower rate at the central bank. The more favorable alternative is to lend the excess liquidity to banks that are short at the higher interbank rate. Hence, banks may not necessarily be willing to bid aggressively in auctions when liquidity is more sparsely distributed. Although this finding is specific to the Norwegian setting, it nevertheless highlights the importance of central bank implementation frameworks (Åberg et al., 2021).

The remainder of the paper proceeds as follows. Section 3.2 provides the relevant institutional background on the NB reserve management system and collateral framework. Section 3.3 describes the data used in the analysis. Section 3.4 presents the empirical analysis, and section 3.5 concludes.

3.2 Institutional background

3.2.1 Reserve management system

NB operates a quota system introduced on 3rd October 2011 to manage bank reserves. The primary objective of a quota-based system is to stimulate the redistribution of reserves in the interbank market. Banks are classified into three quota groups based on their respective assets, and their quotas collectively sum to NOK 45 bn.[4] All banks in the same group are assigned the same quota except settlement banks, which have supplemental quotas.[5] Quotas are revised every six months and come into effect in April and October each year. All reserves below the quota are remunerated at the prevailing policy rate, and reserves over the quota are remunerated at the reserve rate, which is 100 basis points below the policy rate.

NB aims to maintain the aggregate level of reserves at NOK 35 bn. with a symmetrical interval of ±5 bn. This is set below the total quota to provide NB flexibility in managing reserves.[6] Transfers to and from the government's account at NB can result in significant fluctuations in the aggregate stock of reserves. Figure 3.1 shows the daily development of aggregate banking reserves over the sample period. While the aggregate stock of daily reserves is rather volatile, the average lies within the target interval of NOK 30 - NOK 40 bn.

[INSERT FIGURE 3.1]

To steer reserves toward the target level, NB develops a forecast of structural liquidity, which refers to the total amount of banking reserves in the absence of NB's liquidity-injecting or -depleting market operations. When structural liquidity is expected to fall below the target level, for instance, due to tax payments to the Norwegian state, NB adds liquidity through liquidity-providing fixed-rate auctions (known as F-loan auctions). Conversely, when structural liquidity is expected to rise above the target level, for instance, due to pension payments from the Norwegian state, NB withdraws liquidity through liquidity-draining fixed-rate auctions (known as F-deposit auctions).

Auctions are usually announced in the morning or a day ahead when structural liquidity is expected to deviate from the operational target for total liquidity. They are of a relatively short maturity and follow an American-style arrangement, where participants can submit multiple bids at various prices and quantities before the close of the auction. Auctions typically settle on the same day as they occur. The NB prevailing policy rate forms the ceiling for the minimum acceptable bid rate in F-loan auctions and the maximum acceptable bid rate in F-deposit auctions.

[4] Over the sample period, the composition of banks in each quota group remained similar.

[5] The additional quota for the settlement bank is proportional to the total assets of the banks for which it performs settlements. The two settlement banks throughout the sample include DNB Bank ASA and SpareBank 1 SMN. Starting in October 2015, Danske Bank was also designated as a settlement bank.

[6] This also ensures that abrupt fluctuations in the reserves do not adversely affect short-term interest rates. If Norges Bank is successful in keeping total reserves at NOK 35 bn., each bank should, on average, have close to 78% of its quota filled up.

Figure 3.2 shows the annual amount of liquidity injected and withdrawn through the F-loan and F-deposit auctions, respectively, from October 2011 to April 2016. The significant liquidity volumes underscore the importance of liquidity auctions in steering reserves towards the target level. We also observe that, generally, the amount of liquidity withdrawn through F-deposit auctions is higher than the amount injected through F-loan auctions in a given year.

[INSERT FIGURE 3.2]

By redistributing reserves among themselves, banks can hold deposits in NB within the quota, with the result that no bank has to deposit reserves overnight at the reserve rate or borrow overnight at the central bank overnight lending rate, which is 100 basis points above the policy rate. The interbank overnight rate, commonly known as NOWA, lies between the reserve and the overnight loan rates, i.e., close to the policy rate.[7] This is evident from Figure 3.3, which shows the time-series evolution of the different rates since the start of the quota regime until the end of the sample period in April 2016. Aside from occasional peaks at quarter and year ends, the NOWA rate lies just below the policy rate with an average spread of about negative one basis point over the entire sample period.

[INSERT FIGURE 3.3]

3.2.2 Collateral framework

NB operates a uniform collateral framework across all its lending facilities, including F-loan auctions. The banks' total borrowing capacity from NB corresponds to the haircut-adjusted value of their pledged collateral. The collateral is pledged into a pool, with lending collateralized by the value of the whole pool and not linked to individual assets. Banks can swap one collateral type for another in the pool as long as it is deemed eligible by the central bank. However, securities already pledged as collateral with another counterparty cannot be re-used as collateral with NB. NB accepts a wide array of securities across different asset classes, credit ratings, currencies, and issuers as eligible collateral. The eligible collateral list is updated daily and is publicly available on the NB website.

Securities must meet certain requirements to qualify as eligible collateral. First, the securities must be denominated in Norwegian kroner (NOK) or the following foreign currencies: Swedish kroner, Danish kroner, Euro, US Dollar, Japanese Yen, Australian Dollar, New Zealand Dollar, and Swiss Franc. Second, the lowest acceptable credit rating for foreign-issued bonds is A from S&P or the equivalent rating from Fitch or Moody's, while the lowest acceptable credit rating for domestic-issued bonds is BBB- from S&P or the equivalent rating from Fitch or Moody's.[8]

[7] NOWA stands for Norwegian Overnight Weighted Average rate and is based on realized unsecured overnight loans in the Norwegian interbank market.

[8] For reference, a single A rating from the S&P corresponds to an Aa3 rating on the Moody's scale and an A+ rating on the Fitch scale.

Third, securities denominated in NOK must have a minimum volume outstanding of NOK 300 million, and securities denominated in a foreign currency must have a minimum volume outstanding equivalent to EUR 100 million. Fourth, a bank may not pledge bonds, notes, or short-term paper that are issued by companies of which the bank, or a bank in the same group, indirectly or directly owns more than 1/3.[9]

Securities are divided into four categories based on their perceived riskiness. Within each category, the haircut depends on the security's maturity and fixed rate period. Notably, the security haircut is independent of the credit risk of the counterparty pledging it. Generally, securities in higher categories, with longer maturity and fixed interest rates receive higher haircuts. Securities denominated in foreign currency receive an additional haircut of 5%. All asset-backed securities (ABSs) are subject to a 15% haircut, regardless of maturity. Finally, additional haircuts apply to securities that do not have sufficient price information. In these cases, the value is determined based on the nominal value, less an additional haircut depending on the security's rating. The haircut rules effective from 15th February 2012 are summarized in Table 3.1. There were no significant changes in the collateral policy throughout the study period.

[INSERT TABLE 3.1]

Figure 3.4 depicts the time-series composition of the pledged collateral pool at NB based on the haircut-adjusted value in Panel A and the unique count of pledged securities in Panel B. Covered bonds account for the highest portion of the aggregate collateral value with an average share of 60%. This is followed by foreign government securities (13%), Norwegian government securities (8.5%), and other bonds (8%). While asset-backed securities constituted close to 12% of the collateral value at the beginning of the sample, their presence has gradually diminished over the years to a nearly negligible level. We observe a significant reduction in the number of unique securities pledged as collateral with NB starting mid-February 2012 when the new collateral guidelines were enforced. This change is mainly attributed to a sharp drop in bank bonds, which became ineligible.

[INSERT FIGURE 3.4]

3.3 Data description

Below, we briefly outline our data sources and the data selection process. For the bidding analysis, our sample comprises banks that participate at least once in F-loan auctions from the introduction of the quota system in October 2011 until February 2016.

[9]Covered bonds, however, are exempted from this ruling. A bank may pledge covered bonds as collateral with NB, subject to an additional 5% haircut, even if they are issued by the same bank or by an entity that is part of the same corporate group as the bank.

3.3.1 Data sources

First, we obtain detailed bid-level F-loan auction data from NB for each participating bank, including the timestamp, price, volume, and acceptance status of each submitted bid. Over our sample period, there are 1542 submitted bids from 35 unique banks across 193 F-loan auctions.

Second, we have data on banks' pledged collateral pool with NB. This dataset is only available from 19th December 2011, which marks the start of our sample period. The information is at the ISIN level and includes various security characteristics, including but not limited to haircut, notional values, credit rating, category, currency, maturity, and price. This dataset is available for 130 banks and covers all banks that participate in the F-loan auctions.

Third, we have intraday data on the banks' deposit balances at NB. For each bank, we observe its start-of-the-day balance (5.30 am) and the cumulative deposits or withdrawals at 15-minute intervals until the end of the day (4.30 pm). We supplement bank deposits with their quotas publicly available on the NB website.

Fourth, we have monthly data on the bank balance sheet and quarterly data on the income statement over our entire sample period.

Fifth, we obtain data on banks' security holdings at the Norwegian central security depository and foreign security depositories, including Clearstream and Euroclear. This dataset is acquired from the Statistical Bureau of Norway. It is available at a monthly frequency for the majority of banks that pledge collateral with NB over the period from January 2013 to July 2015. We supplement the security holdings data with eligible collateral data from NB for the same period. It contains the stock of securities that qualify as eligible collateral based on NB collateral rules, along with their associated haircut.

We merge these datasets based on standardized bank names. Together, these datasets enable us to derive a granular view on auction-participating banks regarding their collateral, liquidity, and bank characteristics. Our final sample consists of 34 banks that participate across 175 F-loan auctions.

In addition, we collect daily data on NOK foreign exchange rates, NOWA rate, NOWA volumes, and the Norwegian treasury bill rate from the NB website.

3.3.2 Descriptive statistics

Panel A in Table 3.2 presents summary statistics for F-loan auctions over the sample period. The median allotted volume in the auction is NOK 11.3 bn., which represents approximately 32% of the target banking reserves. This underscores the importance of F-loan auctions in channeling liquidity to the banking system. The median award ratio is 1, suggesting that the total demand for liquidity is usually balanced by the total supply of liquidity in the auctions. However, there is notable dispersion in the award ratio across auctions. The median auction maturity is three days, with a standard deviation of about six days. This indicates the rather short-term nature of F-loan auctions, which is consistent with the fact that these auctions are primarily offered to offset temporary deviations in banking reserves. Moreover, the median number of participating banks and submitted bids in the auction are 6 and 8, respectively, suggesting that, on average, banks submit more than one bid in an auction.

Panel B reports summary statistics for banks that participate in F-loan auctions. We first calculate the time-series average at the bank-level and then report the cross-sectional statistics across all bidding banks. The median bid and accepted volume for a bank are NOK 0.19 bn. and 0.17 bn., respectively. The median award ratio is 0.88, suggesting that banks' demand for liquidity is not typically fully met in these auctions. The mean coverage ratio, which captures the extent to which banks' borrowing capacity from NB (based on the haircut-adjusted value of collateral net of any outstanding loans) exceeds their bid volume, is 7.96 with a standard deviation of 6.06. This indicates that banks pledge significantly more collateral with NB than required. As banks utilize the same collateral pool for intraday borrowing from NB, they may deposit surplus collateral for precautionary reasons. Alternatively, it may reflect limited use for much of the submitted collateral outside NB.

Normalized demand and normalized award represent banks' bid and accepted volume as a percentage of assets or quotas. Economically, these variables proxy for the banks' demand for liquidity relative to their size or quota. The mean estimates for normalized demand and normalized award in terms of assets are 1.15% and 0.93%, respectively. The median estimates of normalized demand and normalized award in terms of quota are 92% and 68%, respectively. This implies that banks' bid volumes represent a significant fraction of their quotas.

[INSERT TABLE 3.2]

Next, we turn to variables that characterize the bidders' price for liquidity - overpricing and premium. They measure how much more the bidder pays or offers for central bank liquidity compared to the contemporaneous policy rate of NB or the NOWA rate.[10] While overpricing only takes into account successful bids by a bank, premium takes into account all submitted bids by a bank, regardless of acceptance. Each of these measure is weighted by the bank's respective bid volume. Economically, these variables indicate banks' willingness to pay for liquidity. The mean overpricing and premium, relative to the policy rate, are 2.71 and 1.99 basis points, respectively. Meanwhile, the mean overpricing and premium, relative to the NOWA rate, are 2.43 and 2.21 basis points, respectively. There is notable variation in overpricing across banks, with standard deviations of 4.14 and 5.44 basis points relative to the policy rate and NOWA, respectively. This indicates that banks differ in willingness or ability to pay for liquidity.

Finally, the mean and median participation rates are 17.86% and 9.94%, respectively. This suggests that most banks participate rather infrequently in F-loan auctions. Larger banks generally participate more often than small banks. The mean participation rate among the ten largest banks based on assets is 35%.

[10]We refer to these as overpricing/premium as the bid rates are generally above the NB policy and NOWA rates.

Panel A in Table 3.3 compares market conditions on days when F-loan auctions are held against non-auction days. We observe that the aggregate average start-of-day reserves on the auction days are lower than those outside. The average difference in reserves normalized by the total quotas is 3.84% (equivalent to NOK 1.72 bn.). This is consistent with the purpose of F-loan auctions, which are held to funnel liquidity when the aggregate reserves fall below the target range.

Next, we observe that the NOWA-policy spread is about one basis point lower, and interbank volumes are NOK 1.31 bn. higher on days when auctions are held. The higher interbank activity indicates a larger redistribution of liquidity among banks on the auction days. This is expected as some banks may end up with surplus liquidity, and others with a shortfall after the close of the auction.

In Panel B, we compare liquidity conditions and characteristics of banks that participate at least once in F-loan auctions against those that never participate. First, banks participating in auctions are noticeably bigger than those that do not engage in auctions. The difference in their assets is economically significant, with participating banks exhibiting mean assets approximately 15 times greater than their non-participating counterparts. Based on the observed mean reserve quotas, large banks belonging to the first and second quota groups have higher representation among auction participants. A possible explanation for the limited engagement of small banks in auctions is that they typically have more stable net flows. Consequently, their reserves do not deviate much from the assigned quota. Alternatively, smaller banks lack the capabilities to participate in loan auctions and instead rely on settlement banks to manage their liquidity needs.

[INSERT TABLE 3.3]

Second, we find that banks participating in auctions have higher leverage than non-participating banks. Third, we observe significant differences in the liquidity position of bidding and non-bidding banks. Banks that participate in auctions have markedly lower reserve balances relative to their respective quota compared to banks that choose not to participate. The average normalized start-of-day reserves of participating banks is around 15% lower than that of non-participating banks. To the extent that a bank's reserve balance relative to its quota proxies for its liquidity needs, it is not surprising that banks that are further away from their quotas are among the auction participants. Fourth, banks participating in auctions have significantly higher borrowing capacity, with an average difference in credit limit of NOK 5.80 bn., compared to non-participants. This reflects the higher liquidity needs of auction participants.

Finally, we characterize the composition of pledged and eligible collateral. Panel A in Table 3.4 presents summary statistics on the characteristics of collateral that banks, both bidding and non-bidding, pledge with NB.[11] For each bank, we first calculate the time-series average and

[11]Table A2 in the Appendix compares the collateral characteristics between bidding and non-bidding banks. With the exception of HHI, we do not find any statistically significant differences in the characteristics of collateral between bidding and non-bidding banks. Hence, it is not the case that only banks with lower or higher quality

then report the cross-sectional statistics across all banks.

The mean volume-weighted average haircut is about 6%, with a cross-sectional dispersion of 1.65%. The pledged collateral pool predominantly consists of NOK-denominated securities, with banks typically holding 96% of their pledged collateral in NOK-denominated securities. This is expected since the NB collateral framework applies more stringent haircuts to securities denominated in foreign currencies. The average bank's share of securities with observable market prices is close to 50% of its pledged pool, which means that NB frequently has to rely upon model-based prices to assess the value of submitted collateral. Norwegian treasury securities account for only about 3% of the average bank's stock of deposited collateral. Moreover, we observe fairly low use of "own" collateral securities. These include covered bonds issued by the pledging bank or entities belonging to the same banking group as the pledging bank.

Next, examining the rating profile of pledged collateral, we observe that the average bank's pledged collateral stock is highly rated with a mean weighted average rating score of about 1.6, where 1 corresponds to an S&P AAA rating. This is particularly important considering the average share of securities in a bank's collateral pool that requires a rating is close to 65%. Most banks have a highly concentrated pledged collateral portfolio, as indicated by the median Herfindahl-Hirschman Index of about 0.78. Finally, the mean weighted average maturity of pledged collateral is about 3.5 years, suggesting that the average security deposited in the pool has a medium-term maturity.

In summary, banks predominantly pledge highly rated collateral, with a significant portion of securities lacking observable market prices and a strong preference for domestic securities.

[INSERT TABLE 3.4]

Panel B shows summary statistics on eligible collateral over the cross-section of all banks. We merge each bank's security holdings data with the NB-eligible and pledged collateral datasets. This combined dataset is available for 107 banks from January 2013 to July 2015. There are 11 thousand unique ISINs in the holdings data, of which only 7.5% are on the eligibility list. Approximately 90% of the eligible collateral is pledged with NB during the sample period. For the median bank, we are able to identify their entire pledged collateral stock from within their eligible holdings dataset as denoted by the median match ratio of 1.[12]

Banks face varying constraints when selecting the securities they want to pledge with NB. Those with a higher stock of eligible securities relative to their liquidity needs have greater flexibility in their collateral allocation decision than those with a smaller stock. We proxy this based on the ratio of securities pledged with NB to the total stock of eligible securities in each

collateral self-select into F-loan auctions.

[12] There is a total of 3 banks where the match ratio is less than 0.75. In principle, we should be able to achieve a complete match for all banks in our sample. However, given the monthly frequency of our security holdings dataset, it could be the case that a security pledged as collateral with the NB during the month was sold off before the end of the month and, hence, does not show up in the holdings dataset.

bank's portfolio. The complement of this ratio captures the pledging capacity of a bank, where a higher value indicates higher flexibility in the choice of collateral. The mean and median capacities are 35% and 27%, respectively, with a standard deviation of 27%. This implies that banks have some degree of flexibility in choosing what type of eligible collateral to pledge. However, this flexibility exhibits significant variation across banks.

The average bank has only a tiny share of foreign-eligible securities in its portfolio.[13] The mean and median dispersion in the banks' eligible collateral stock are 2.88% and 3.0%, respectively, indicating significant variation in the quality of eligible collateral. The mean haircut of the eligible collateral securities is about 14 basis points lower than the mean haircut of the pledged collateral securities. If we instead focus on the mean haircut of eligible collateral securities that banks do not pledge with NB, the haircut differential against pledged collateral securities is even lower at 48 basis points.[14] This indicates that banks tend to pledge securities with higher haircuts from within their eligible pool with NB. We explore this more formally in the next section.

3.4 Results and discussion

We begin our analysis by examining the collateral pledging behavior of banks with an account at NB, including both bidding and non-bidding banks. Next, we study how bidding banks' auction outcomes relate to the quality of their pledged collateral and other characteristics.

3.4.1 Collateral quality and pledging behavior

The richness of our data enables us to observe not only the securities that a bank chooses to pledge as collateral with NB but also those that it can potentially pledge from its stock of eligible securities. If lower-quality collateral has a lower outside opportunity cost vis-a-vis higher-quality collateral, we would expect banks to pledge relatively worse-quality securities with the central bank from their eligible pool. We examine this relation through the following logistic regression:

$$Pr(Pledged_{i,j} = 1) = \phi\big(\beta_0 + \beta_1 \text{Haircut}_{i,j} + \epsilon_{i,j}\big) \tag{3.1}$$

where $Pledged_{i,j}$ is an indicator variable denoting if security i is pledged as collateral with NB by bank j and zero otherwise. $Haircut_{i,j}$ is the haircut associated with security i held by bank j. $\phi(\cdot)$ is the logistic function. Our main coefficient of interest is β_1, which captures the change in the likelihood of a security being pledged as collateral based on its haircut. We cluster the standard errors at the bank level.

[13] Among the 22 banks with foreign eligible collateral, the average share of foreign holdings is 8.4%.

[14] There are five banks in the sample that pledge everything from their eligible stock hence the number of observations is lower.

The results in column 1 of Table 3.5 show a statistically significant positive relation between security haircut and its likelihood of being pledged with NB. In terms of economic magnitude, a one percent increase in security haircut results in the odds of being pledged with NB by a factor of 1.03 ($e^{0.03}$). In other words, for a one-percent increase in security haircut, the odds of being pledged with NB increase by approximately 3%. This represents an economically significant change.

[INSERT TABLE 3.5]

In column 2, we include bank fixed effects to account for the unobserved heterogeneity between banks. This is important as banks likely have different liquidity needs and collateral constraints, which may affect their pledging behavior.[15] The coefficient estimate on haircut becomes twice as large as in column 1. These results suggest that banks strategically pledge relatively worse securities with the central bank from their eligible pool, possibly due to the central bank's more favorable haircut assignment relative to the market.

NB assigns a higher haircut for foreign securities than domestic securities of comparable quality. Hence, it may be that our results are mainly driven by banks that pledge foreign securities. To address this, we restrict the sample to only those banks without foreign eligible securities in column 3. This results in a substantial drop in the sample size, from 6000 to 2800, but the number of banks is still quite large at 80. The economic magnitude of the coefficient on haircut remains the same, which suggests that banks with only domestic collateral also exhibit strategic behavior in their collateral pledging decision.

Next, we switch our focus to those banks with positive holdings of foreign eligible collateral. These banks can choose between domestic and foreign collateral in their pledging decision. We are interested in examining whether haircut has a differential effect on the likelihood of being pledged for foreign collateral relative to domestic collateral. Given that the foreign repo market is more mature relative to the Norwegian repo market, pledging foreign collateral with NB likely carries a higher opportunity cost. However, it may also be the case that foreign securities are more difficult to pledge in the Norwegian repo market due to their perceived currency risk and, therefore, carry a lower opportunity cost. We expand equation (3.1) by introducing an interaction term between *foreign* and *haircut*, where foreign is an indicator for foreign-eligible securities.

The results are reported in column 4 of Table 3.5. The coefficient on the interaction term is positive and highly significant. This suggests that for foreign securities, the haircut has a more amplified effect on the likelihood of being pledged relative to domestic securities, providing additional support for our main finding.

As discussed earlier, banks face different constraints with respect to the type of securities they want to pledge with NB. Those with a higher capacity may be more strategic in their pledging behavior than those with lower capacity. Conversely, banks with higher capacity may

[15] This also leads to the loss of five banks that pledge everything from their eligible stock.

be less discriminate or simply indifferent in their pledging behavior, as they are not collateral constrained. We explore this relation by augmenting equation (3.1) with an interaction term between *haircut* and *capacity*. Additionally, we control for potential heterogeneity in the quality of eligible collateral. This is important because banks with higher capacity may not necessarily engage in more strategic pledging behavior if their eligible collateral pool is of a homogenous quality.

Column 5 reports the results. Our main coefficient of interest, *Haircut* × *Capacity*, has a negative sign, but it is not statistically significant. Next, in column 6, we discretize the capacity variable into two groups - high and low, where "high" denotes banks with more than 25% available capacity. Here again, we observe a negative coefficient sign on *Haircut* × *High Capacity*, but it is not statistically significant. Nevertheless, the coefficient on haircut remains statistically significant, and its economic magnitude becomes even stronger. The lack of statistical significance on the interaction term suggests that the relation between the security haircut and its likelihood of being pledged with the central bank is not conditional on the available capacity of the bank. In other words, banks demonstrate similar pledging behavior regardless of their flexibility.

We also consider whether banks participating in F-loan auctions have greater incentives to economize on collateral usage. These banks need to pledge collateral over a more extended period than banks, which primarily deposit collateral with NB to cover their intraday liquidity needs. Hence, we could expect auction-participating banks to engage in more opportunistic pledging behavior. Moreover, these banks may also possess a higher level of sophistication and, therefore, be more strategic in their collateral usage. We supplement equation (3.1) by introducing an interaction term between haircut and alternate proxies for auction participation. We additionally control for the banks' pledging capacity and the dispersion in collateral quality.

[INSERT TABLE 3.6]

The results are reported in Table 3.6. In column 1, auction participation is captured by an auction dummy, which equals one for banks that participate at least once in F-loan auctions over the sample period and zero otherwise. Next, in column 2, we proxy auction participation based on the total participation rate in F-loan auctions over the sample period. Finally, since most banks participate rather infrequently in F-loan auctions, we discretize the total participation rate variable into two groups in column 3 - frequent and infrequent participant. Here, "frequent" denotes banks with a participation rate above 25%. Our main variable of interest is the interaction term between haircut and either of the three auction participation proxies. The coefficient estimate on the interaction term is not statistically significant across any of the three specifications. This suggests that the relation between haircut and pledging behavior is independent of the banks' participation status in F-loan auctions.

Overall, our findings show that banks consider the opportunity cost of collateral when choosing the type of collateral they wish to deposit with the central bank. Securities with lower outside options are more likely to be pledged with the central bank; however, this relation is independent of the banks' pledging capacity and participation in loan auctions. The result underscores the importance of the central bank collateral framework. It supports the view that central bank collateral policies may incentivize banks to engage in strategic pledging if their terms are deemed generous.

3.4.2 Collateral Quality and price of liquidity

In this section, we examine the role of collateral quality on the bidding behavior of banks in the F-loan auctions. As banks seek to economize collateral usage, they may potentially bid more aggressively when pledging relatively lower-quality collateral with the central bank. Essentially, banks have an incentive to bid at higher prices as long as the opportunity cost of pledging collateral with the central bank is lower than the outside option. The worse the collateral quality, the higher the potential for exploiting such differences in opportunity cost. We proxy the price of liquidity using two different but closely related measures - *overpricing* and *premium*. They capture banks' willingness to pay for liquidity in F-loan auctions relative to the contemporaneous policy rate. We estimate the following panel regression:

$$Price_{j,a} = \beta_0 + \beta_1 Haircut_{j,a} + \beta_2 X_{j,a} + \beta_3 Y_a + \beta_4 Z_a + \epsilon_{j,a} \tag{3.2}$$

where $Price_{j,a}$ denotes the price of liquidity based on either of the two proxies submitted by bank j in auction a. $Haircut_{j,a}$ is the volume-weighted average haircut of pledged collateral by bank j at auction a. The vector $X_{j,a}$ captures bank characteristics, including the logarithm of lagged assets; lagged return on equity; daily start-of-day reserves expressed as a percent of quotas; 60-day standard deviation in normalized reserves; an indicator for settlement banks; an indicator for foreign banks; logarithm of bid volume; auction participation rate; and an indicator for participation in the previous F-loan auction. The vector Y_a captures auction characteristics, including auction term expressed in days; logarithm of auction size; an indicator for auctions held at year-end; and an indicator for overlapping auctions. Finally, the vector Z_a captures market conditions, including dispersion in normalized reserves across all banks that have an account with the NB and the TED spread on auction days. A complete description of the variables is enclosed in Table A1 in the Appendix.

The results are reported in Table 3.7. Columns 1 and 2 proxy the price of liquidity based on overpricing, and columns 3 and 4 proxy the price based on premium. We report results with auction fixed effects in columns 1 and 3 and without in columns 2 and 4. The standard errors are clustered at the bank level to account for potential correlation in residuals. For brevity, we only report statistically significant coefficients. For robustness, we also report results excluding the largest Norwegian bank, DNB in Table A3 in the Appendix.[16] Our results remain qualitatively

[16] As of the year-end 2011, DNB accounted for more than 30 percent of the total domestic lending (Norges Bank, 2013).

similar.

[INSERT TABLE 3.7]

Our primary variable of interest, haircut, has the expected positive sign but is not statistically significant in any of the four specifications. This indicates that the banks' willingness to pay for liquidity in auctions is not affected by the quality of their pledged collateral pool, in contrast with the potential mechanism suggested above. A possible explanation could be the design of the NB collateral framework, which does not require earmarking of collateral. Hence, we do not know the exact composition of pledged collateral against each submitted bid. Moreover, as previously discussed, banks usually deposit more collateral in their pool than needed to secure the liquidity demanded in loan auctions. On average, banks deposit 75% more collateral than required. These artifacts obscure the relation between bid price and collateral quality, making it harder to detect.

In the remainder of this section, we discuss additional findings from the regressions in Table 3.7. We find that normalized reserves, which represent a bank's start-of-day reserve balance as a percent of its quota, is inversely related to the price of liquidity. This implies that banks further away from their respective quotas engage in more aggressive bidding as they are more likely to be short. A one standard deviation increase in normalized reserves contributes to a 0.21 basis point (0.01×21) reduction in overpricing, which accounts for approximately 8% of the mean and 10% of the median overpricing.

Consistent with Fecht et al. (2011), we find that smaller banks engage in more aggressive bidding. Smaller banks have access to fewer funding sources outside central bank liquidity operations and may, therefore, be willing to pay higher prices to secure their liquidity needs. The coefficient on the auction participation rate, a proxy for the banks' degree of experience or sophistication in loan auctions, is negative and highly statistically significant. This suggests that banks that frequently participate in loan auctions tend to bid more strategically and consequently pay a lower price of liquidity.[17] We observe a positive and statistically significant association between bid volume and price. Given the competitive setup of F-loan auctions, this is expected. Nevertheless, controlling for bid volume is important for inferring other variables' effects on the price of liquidity.[18]

The next set of results pertains to the specification without auction fixed effects, i.e., columns 2 and 4. We are interested in examining how the price of liquidity depends on auction characteristics. First, we observe that auctions with higher allotted volume are associated with lower prices. This implies that banks tend to bid less aggressively when more liquidity is on

[17]The results are qualitatively similar if we instead use cumulative participation rate, which represents the percentage of previous auctions a bank has participated in.

[18]One could argue that as the banks' bid volumes increase, they need to tap into collateral with a higher opportunity cost, which could result in less aggressive bidding. We explore this by interacting the logarithm of bid volume with haircut and do not find a significant relation.

offer. While banks may not know the exact size of the auction beforehand, they can develop a reasonable estimate based on NB structural liquidity forecasts, published weekly and available to the public.

Second, the price of liquidity is higher for longer-term auctions. The alternative to loan auctions is borrowing from the interbank market, which carries rollover risk due to its overnight structure. Therefore, banks may be willing to pay more when they can secure liquidity for the longer term.

Third, auctions held at the end of the year are significantly more expensive. The overpricing in auctions held at year-end is, on average, 12.8 basis points higher than the rest of the year. This is consistent with a growing body of research, which documents that banks tend to engage in window-dressing behavior at year-ends and may become reluctant to lend to each other.

Finally, we examine how market conditions affect the price of liquidity. The coefficient on imbalance, which measures the dispersion in the distribution of normalized reserves across banks, is positive but not statistically significant. This indicates that the price of liquidity paid by banks in loan auctions is unrelated to its distribution across banks.[19] This stands in contrast with Fecht et al. (2011), who find that banks bid more aggressively in Eurosystem repo auctions when liquidity is less evenly distributed.

The difference in result could be due to differences in the institutional setting. Unlike the Euro area, banks in Norway are not subject to reserve requirements. Under the liquidity-neutral regime, a higher imbalance implies that some banks face a liquidity shortage while others have a surplus. Banks with excess liquidity can either deposit it with NB at the reserve rate or lend to banks in need through the interbank market at the more favorable NOWA rate. Consequently, banks may lack incentives to bid aggressively in F-loan auctions when liquidity is more sparsely distributed, as they can secure their needs through the interbank market. In the Euro area, reserves are calculated based on daily averaging over the maintenance period. This implies that when there is a greater imbalance in the distribution of reserves, a bank with excess liquidity may not always have the incentives to lend to another bank with a liquidity shortfall due to reporting considerations.

An alternative explanation for the difference could be the disparity in the extent of imbalance between the Euro area and Norway. Based on the summary statistics reported in Fecht et al. (2011) Table 5, the coefficient of variation for imbalance - a measure of relative variability - is approximately six times higher in the Euro area compared to Norway. This implies that liquidity distribution across banks in the Euro area is significantly more uneven than in Norway. Consequently, the price of liquidity that Norwegian banks pay in auctions is less affected by its cross-sectional distribution than that for banks in the Euro area.[20] Consistent with our

[19]We also interacted imbalance with bank size to examine if smaller banks are more vulnerable in more imbalanced markets. The coefficient sign on the interaction term is negative but not statistically significant.

[20]The coefficient of variation is calculated as standard deviation normalized by the mean. While the coefficient of variation in Fecht et al. (2011) is 2.91, it is only 0.46 in our study.

expectation, we find that when there is greater perceived risk in the interbank market as proxied by the TED spread, the price of liquidity is higher.

Overall, our results indicate that the banks' willingness to pay for liquidity is not affected by the quality of their pledged collateral and the aggregate distribution of liquidity but rather by their individual liquidity position and auction characteristics.

3.4.3 Collateral quality and liquidity uptake

Fecht et al. (2016) show that banks with lower-quality collateral obtain disproportionately larger amounts of liquidity in the Eurosystem repos, which the authors interpret as suggestive evidence for systemic arbitrage. We explore how this relation holds in an institutional environment, where reserve requirements do not bind and the banks, as such, do not face a hard constraint. We proxy banks' liquidity uptake in auctions based on their bid volume normalized by total assets. *Normalized demand* takes into account the total submitted bid volume, and *Normalized award* only takes into account the successful bid volume. We estimate the following panel regression:

$$Uptake_{j,a} = \beta_0 + \beta_1 Haircut_{j,a} + \beta_2 X_{j,a} + \beta_3 Y_a + \beta_4 Z_a + \epsilon_{j,a} \tag{3.3}$$

where $Uptake_{j,a}$ denotes the liquidity uptake based on either of the two proxies by bank j in auction a. Variables on the right-hand side are similar to those in equation (3.2) with certain omissions, including the logarithm of bid volume and total participation rate. The results are reported in Table 3.8. Columns 1 and 2 proxy liquidity uptake based on normalized award, and columns 3 and 4 proxy liquidity uptake based on normalized demand. Results with auction fixed effects are reported in columns 1 and 3 and without in columns 2 and 4. The standard errors are clustered at the bank level. We only report coefficients that are statistically significant. For robustness, we also report results excluding the largest Norwegian bank, DNB in Table A4 in the Appendix. Our results remain qualitatively similar.

[INSERT TABLE 3.8]

In line with Fecht et al. (2016), we find a positive and statistically significant coefficient on haircut across all four specifications. The economic magnitude of the coefficient is similar in the specification with and without auction fixed effects, suggesting that it is not driven by unobserved heterogeneity across auctions. Banks with lower-quality collateral systematically obtain more liquidity in central bank liquidity auctions relative to the size of their assets. In terms of effect size, a one standard deviation increase in haircut corresponds to a 0.19% (0.13×1.44) increase in normalized award, which accounts for approximately 20% of the mean and 25% of the median normalized award. This could be attributed to the lower opportunity cost of lower-quality collateral due to its perceived lax haircut treatment by the central bank. An alternative explanation could be that banks' collateral quality degrades as they obtain more liquidity in auctions. However, this explanation seems less plausible if banks strategically allocate worse quality collateral in their pledged pool, as shown in our analysis above on collateral pledging behavior.

Regarding other bank characteristics, we find that smaller banks have higher liquidity uptake as they likely have limited funding alternatives outside central bank auctions. This is consistent with our earlier finding on the higher price of liquidity by smaller banks. Next, we observe that banks with higher leverage (i.e., lower equity ratio) obtain more liquidity in auctions. These banks likely face higher funding costs in the market and may consequently have greater incentives to obtain more liquidity in central bank auctions to satisfy their needs. Moreover, banks further away from their quota also borrow more in auctions. Interestingly, foreign banks obtain significantly more liquidity than domestic banks. This may be because foreign banks have lower access to NOK-denominated liquidity sources, such as customer deposits, than domestic banks.

The results on auction characteristics indicate that larger auctions are associated with higher liquidity uptake. This suggests that F-loan auctions are effective in funneling liquidity into the banking system.[21] Next, while banks submit higher bid volume in auctions held at the end of the year, the successful bid volume is not any higher or lower. There is likely more competition for liquidity at year-end due to window dressing concerns, and as a result, the liquidity acquired is significantly less than the liquidity sought. Finally, auctions with overlapping maturity have lower liquidity uptake. These are likely fine-tuning auctions conducted late in the day, with lower allotted volume.

To summarize, our results show that smaller banks with higher leverage and possessing worse-quality collateral have a disproportionally larger liquidity uptake from the central bank.

3.5 Conclusion

Central bank collateral rules aim to ensure that banks have sufficient access to central bank liquidity while mitigating the risk exposure of the central bank. However, if the central bank assigns haircuts on collateral securities that do not adequately reflect market conditions (typically lower), it could incentivize banks to pledge relatively riskier securities with the central bank. This is plausible, as central banks do not frequently adjust haircuts on eligible securities. Moreover, since a large number of eligible collateral securities are not actively traded, there is limited scope for market forces to define the terms under which the central bank provides liquidity to the banking system. As highlighted in Nyborg (2016), an accommodative collateral framework could distort market discipline or, worse, stimulate the production of lower-quality assets.

Using proprietary data that links banks' pledged and eligible collateral securities, we find that banks tend to pledge lower-quality collateral from their eligible stock with the Norges Bank.

[21] In a way, this result is to be expected as F-loan auctions are held to counterbalance the effect of temporary deviations in banking reserves. The greater the scope of these deviations, the larger the allotted auction volume and, consequently, the higher the banks' liquidity uptake.

This supports the idea that banks may engage in strategic pledging if the central bank collateral terms do not adequately reflect market conditions.

We also examine how collateral quality interacts with banks' bidding behavior in Norges bank liquidity auctions. Our results indicate that banks with higher leverage and worse pledged collateral quality acquire disproportionally more liquidity in auctions. This is consistent with the systemic arbitrage hypothesis in Fecht et al. (2016). Importantly, our results show that systemic arbitrage is not merely a crisis phenomenon but is also present during a period of economic normalcy.

However, we do not find that banks with lower-quality pledged collateral bid more aggressively in the liquidity auctions. Instead, the price of liquidity is related to the individual liquidity position of banks and auction characteristics. Bidding is more aggressive for auctions held at year-end, likely due to banks' reluctance to engage in interbank lending for reporting considerations. Unlike Fecht et al. (2011), we do not find that the price of liquidity is related to its cross-sectional distribution. This finding signifies the role of central bank implementation frameworks.

Overall, our results underscore the importance of the central bank collateral framework for liquidity provision. Although the collateral rules established by Norges Bank are relatively stringent, there is still scope for banks to capitalize on differences in the opportunity cost of collateral. While such differences may be mitigated through continuously adjusting collateral haircuts based on market input, it may not be feasible as a substantial portion of eligible collateral securities do not actively trade in the market. Alternatively, the Norges Bank could discourage the use of riskier collateral by imposing an additional surcharge for pledging lower-quality collateral.

3.6 Tables and Figures

Table 3.1: Haircut Schedule

The table shows the haircut that Norges Bank assigns to a security based on its category and other characteristics. It reflects the rules as of 15th February 2012.

Category 1: government securities of AAA rating, funds only invested in AAA securities
Category 2: government securities with a credit rating AA+ to A, covered bonds with a credit rating AAA to AA-, local/regional government securities, foreign local government securities with a minimum rating of A (S&P) or equivalent, securities with risk weight 0, government-guaranteed securities, securities issued by private entities with a rating of AAA
Category 3: securities by foreign private foreign issuers with a rating from AA+ to A, covered bonds with a rating A+ to A, securities by Norwegian private issuers with a rating AA+ to A, funds that are eligible
Category 4: unrated covered bonds by Norwegian issuers, covered bonds by Norwegian issuers with a rating of A- or lower, securities by private Norwegian issuers with a rating of A- to BBB-

	Category 1 *Least Risky*		Category 2		Category 3		Category 4 *Most Risky*	
Maturity (Years)	Fixed	Floating	Fixed	Floating	Fixed	Floating	Fixed	Floating
0-1	1	1	3	3	4	4	8	8
1-3	3	1	5	4	6	5	11	10
3-7	5	1	7	5	10	7	17	14
7+	7	1	10	6	13	9	22	17

Table 3.2: Auction Summary Statistics

This table reports summary statistics for F-loan auctions in Panel A and for F-loan auction participants in Panel B. For each reported variable in panel B, we first calculate the time series average at the bank-level and then report the cross-sectional statistics across all bidding banks. *Allotted Volume* is the amount of liquidity allotted in the auction. *Bid Volume* captures the total amount of liquidity bid in an auction in Panel A, and the amount of liquidity bid by a bank in Panel B. *Award Ratio* captures the ratio of allotted to bid volume for an auction in panel A and the ratio of accepted to bid volume for a bank in panel B. *Maturity* is the term of auction in days. *Banks* is the number of participating banks in an auction. *Bids* is the number of submitted bids in an auction. *Coverage Ratio* is the ratio of a bank's credit limit to its bid volume. *Normalized Demand* and *Normalized Award* represent the bank submitted and accepted bid volume as a percent of its assets or quota, respectively. *Overpricing* is the difference between the volume-weighted average bid rate of a bank conditional on successful bids relative to the policy or NOWA rate. *Premium* is the difference between the volume-weighted average bid rate of a bank based on all submitted bids relative to the policy or NOWA rate. *Participation Rate* is the number of auctions that a bank participates in as a percent of all auctions held over the sample period.

Panel A: Auction Statistics

	Observations	Mean	Median	SD	Min	Max
Allotted Volume (Bn.)	179	14.23	11.30	9.68	0.07	53.00
Bid Volume (Bn.)	179	17.18	14.47	10.92	0.07	57.83
Award Ratio	179	0.85	1.00	0.20	0.31	1.00
Maturity (days)	179	5.00	3.00	6.39	1.00	42.00
Banks	179	5.97	6.00	2.99	1.00	17.00
Bids	179	8.23	8.00	4.66	1.00	23.00

Panel B: Bidding Bank Statistics

	Observations	Mean	Median	SD	Min	Max
Bid Volume (Bn.)	34	0.98	0.19	2.27	0.01	10.77
Accepted Volume (Bn.)	34	0.83	0.17	1.85	0.00	8.31
Award Ratio	34	0.80	0.88	0.23	0.00	1.00
Coverage Ratio	34	7.96	6.82	6.06	1.13	25.10
Normalized Demand - Assets (%)	34	1.15	0.99	0.65	0.44	3.65
Normalized Award - Assets (%)	34	0.93	0.74	0.62	0.00	3.17
Normalized Demand - Quota (%)	34	111.38	92.33	77.00	20.00	325.33
Normalized Award - Quota (%)	34	95.93	68.39	76.85	0.00	281.50
Overpricing Policy (bps)	34	2.71	2.02	4.14	0.00	25.00
Overpricing NOWA (bps)	34	2.43	1.86	5.44	-11.00	29.00
Premium Policy (bps)	34	1.99	2.02	1.98	-3.00	10.60
Premium NOWA (bps)	34	2.21	1.76	2.71	-3.50	14.60
Participation Rate (%)	34	17.86	9.94	20.61	0.57	72.73

Table 3.3: Liquidity Summary Statistics

Panel A compares aggregate liquidity conditions on F-loan auction days against non-auction days. Panel B compares liquidity and other characteristics between banks that participate at least once in F-loan auctions over the sample period and those that never participate in F-loan auctions. For each reported variable in panel B, we first calculate the time-series average at the bank-level and then report the cross-sectional statistics across all bidding and non-bidding banks separately. *Normalized Reserves* is the total banking reserves at the start of the day expressed as a percent of aggregate quota in panel A, and a bank's start-of-day reserves as a percent of its respective quota in panel B. *Imbalance* is the cross-sectional dispersion in normalized reserves. *NOWA Spread* is the difference between the Norwegian overnight weighted average rate and the contemporaneous policy rate. *NOWA Volume* is the trading volume in the Norwegian unsecured interbank market in NOK billions. *Reserve Quota* is the assigned quota limit for each bank expressed in NOK millions. *Credit Limit* is the available credit limit based on the haircut-adjusted value of collateral net of any outstanding loans expressed in NOK billions. All other variables are self-explanatory. The *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Auction-level Statistics

	Auction Days			**Non-Auction Days**			**Difference**
	Observations	Mean	SD	Observations	Mean	SD	
Normalized Reserves (%)	182	72.78	11.5	961	76.52	8.08	-3.84^{***}
Imbalance (%)	182	65.34	30.30	961	61.98	26.70	3.36
NOWA Spread (bps)	182	−0.11	3.09	934	−0.91	6.69	0.80^{**}
NOWA Volume (Bn.)	174	14.26	6.53	923	12.95	6.58	1.31^{**}

Panel B: Bank-level Statistics

	Bidders			**Non-Bidders**			**Difference**
Assets (Mn.)	35	103.17	301.55	113	6.85	17.67	96.32^{*}
Equity Ratio (%)	35	8.03	2.49	113	10.87	8.01	-2.84^{***}
Return on Equity (%)	35	6.12	2.07	113	7.36	23.3	-1.24
Reserve Quotas (Mn.)	35	897.16	1656.92	113	146.50	657.55	750.66^{**}
Normalized Reserves (%)	35	71.52	21.20	113	86.86	41.46	-15.34^{***}
Credit Limit (Bn.)	35	6.02	14.22	113	0.22	0.86	5.80^{***}

Table 3.4: Collateral Summary Statistics

Panel A summarizes characteristics of collateral that banks pledge with NB, and panel B shows statistics on eligible collateral from banks with available holdings data. The sample period in panel A spans from December 2011 to April 2016, and panel B spans from January 2013 to July 2015. For each variable shown, I first calculate the time-series average at the bank-level and then report the cross-sectional statistics across all banks. The variables in panel A are self-explanatory. *Match Ratio* is the proportion of a bank's pledged securities with NB that can be matched against its security holdings dataset. *Capacity* is the complement, expressed in percentage, of the ratio between a bank's pledged and eligible collateral stock. *Foreign* is the percent of foreign securities in a bank's eligible collateral portfolio. *Haircut Dispersion* is the standard deviation of security haircut in a bank's eligible collateral pool. *Non-Pledged Haircut* is the haircut based on eligible collateral securities that banks do not pledge with NB.

Panel A: Pledged Collateral Statistics

	Observations	Mean	Median	SD	5th	95th
Haircut (%)	130	6.01	5.81	1.65	3.85	9.61
Maturity (days)	130	1231.79	1243.98	349.59	705.18	1839.69
Credit Rating (1 best)	124	1.64	1.34	1.21	1.00	2.73
NOK Securities (%)	130	96.53	100.00	14.25	75.23	100.00
Fixed-rate Securities (%)	130	6.45	0.00	16.29	0.00	33.60
Norwegian Treas. Securities (%)	130	2.97	0.00	13.52	0.00	9.49
Traded Securities (%)	130	48.11	47.90	17.84	19.70	84.03
Own Securities (%)	130	0.70	0.00	4.64	0.00	1.05
HHI Collateral Category	130	0.76	0.78	0.17	0.45	0.99

Panel B: Eligible Collateral Statistics

	Observations	Mean	Median	SD	5th	95th
Match Ratio	107	0.97	1.00	0.95	0.79	1.00
Capacity (%)	107	34.93	27.40	28.28	0.97	86.24
Foreign (%)	107	1.72	0.00	5.68	0.00	12.41
Haircut Dispersion (%)	107	2.88	3.00	0.81	1.12	3.90
Haircut (%)	107	5.86	5.84	1.03	4.74	7.56
Non-Pledged Haircut (%)	102	5.53	5.53	1.30	3.83	7.54

Table 3.5: Collateral Quality and Pledging Behavior

The following table reports results from the following logistic regression:

$$Pr(Pledged_{i,j} = 1) = \phi(\beta_0 + \beta_1 \text{Haircut}_{i,j} + \sigma_j + \epsilon_{i,j})$$

where $Pledged_{i,j}$ is equal to one if an eligible security i is pledged as collateral with Norges Bank by bank j and zero otherwise. $Haircut_{i,j}$ is the haircut on security i held by bank j expressed as a percentage. σ_i denotes bank fixed effects. The sample includes all banks that have both security holdings and pledged collateral data available for the period starting January 2013 until July 2015. Column 1 reports results from a pooled regression; column 2 reports results with bank fixed effects; column 3 restricts the sample to only those banks without foreign eligible securities. In column 4, we augment the regression specification with an interaction between security haircut and foreign, where foreign is an indicator for foreign-eligible securities. In columns 5 and 6, we introduce an interaction between security haircut and capacity in the regression specification. *Capacity* is the complement, expressed in percentage, of the ratio between a bank's pledged and eligible collateral stock. *High Capacity* is an indicator for banks with capacity above 25%. *Haircut Dispersion* is the standard deviation of haircut in the bank's eligible collateral pool. Z-statistics reported in parentheses are based on standard errors clustered at the bank level. The *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Haircut (%)	0.03**	0.06***	0.06**	−0.02	0.09**	0.09**
	[2.19]	[3.36]	[2.36]	[−0.47]	[2.18]	[2.45]
Foreign				−1.12		
				[−1.47]		
Foreign × Haircut				0.23***		
				[5.99]		
Capacity (%)					−0.04***	
					[−8.88]	
Haircut Dispersion (%)					−0.10	−0.15
					[−1.47]	[−0.94]
Capacity × Haircut					−0.001	
					[−1.11]	
High Capacity						−1.85***
						[−4.64]
High Capacity × Haircut						−0.04
						[−1.02]
Constant	0.16	2.24***	[2.25]***	1.01***	2.10***	1.85***
	[0.96]	[24.12]	[3.10]	[17.77]	[6.46]	[3.10]
Bank FE	No	Yes	Yes	Yes	No	No
Banks	107	102	80	22	102	102
High Capacity Banks						55
Low Capacity Banks						52
Eligible Securities	756	756			756	756
Pledged Securities	690	690			690	690
Domestic Eligible Securities			357	451		
Domestic Pledged Securities			276	426		
Foreign Eligible Securities				301		
Foreign Pledged Securities				247		
Observations	6,096	6,051	2,802	3,249	6,096	6,096

Table 3.6: Collateral Quality and Pledging Behavior Conditional on F-loan Auction Participation

This table reports results from a logistic regression. We augment the regression specification in equation (3.1) with an interaction between security haircut and auction participation. *Auction Participant* is a dummy equal to one for banks that participate at least once in F-loan auctions over the period starting January 2013 until July 2015. *Participation Rate* is the participation rate of a bank in F-loan auctions over the sample period. *Frequent Participant* is a dummy that is equal to one for banks with a participation rate above 25%. *Capacity* is the complement, expressed in percentage, of the ratio between a bank's pledged and eligible collateral stock. *Haircut Dispersion* is the standard deviation of haircut in the bank's eligible collateral pool. Z-statistics reported in parentheses are based on standard errors clustered at the bank level. The *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Haircut (%)	0.03	0.05**	0.07**
	[1.41]	[2.11]	[3.26]
Capacity (%)	−0.05***	−0.05***	−0.05***
	[−20.31]	[−20.56]	[−19.28]
Haircut Dispersion (%)	−0.10	−0.14	−0.08
	[−1.29]	[−1.27]	[−0.86]
Participant	−0.34		
	[−1.44]		
Participation Rate (%)		0.002	
		[0.25]	
Frequent Participant			0.09
			[0.29]
Haircut × Participant	0.04		
	[1.13]		
Haircut × Participation Rate		0.0002	
		[0.45]	
Haircut × Frequent Participant			-0.02
			[−0.59]
Constant	2.54***	2.40***	2.22***
	[10.03]	[7.06]	[6.92]
Non-Action Banks	79	79	
Auction Banks	28	28	
Frequent Auction Banks			10
Infrequent Auction Banks			97
Observations	6,096	6,096	6,096

Table 3.7: Liquidity Price and Collateral Quality

The table reports results from a panel regression. In columns 1 and 2, the dependent variable is *Overpricing*, and in columns 3 and 4, the dependent variable is *Premium*. Both of the variables are expressed in basis points. Column 1 and 3 report results with auction fixed effects, and column 2 and 4 report results without. A detailed description of all variables is enclosed in Table A1 in the appendix. The t-stats reported in parenthesis are based on standard errors clustered at the bank level. The *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Overpricing (bps)		Premium (bps)	
Haircut (%)	0.06	0.06	0.03	0.03
	[1.32]	[1.16]	[0.63]	[0.57]
Normalized reserves (%)	−0.01***	−0.004**	−0.01***	−0.004**
	[−2.60]	[−2.27]	[−2.60]	[−2.40]
ln(Assets) (Bn.)	−0.41***	−0.49***	−0.40***	−0.43***
	[−3.54]	[−3.92]	[−3.21]	[−3.59]
ln(Bid volume) (Bn.)	0.26**	0.35**	0.31**	0.34**
	[2.04]	[2.45]	[2.54]	[2.43]
Participation rate (%)	−0.02***	−0.02***	−0.01**	−0.01***
	[−3.14]	[−3.55]	[−2.35]	[−2.92]
Imbalance (%)		0.003		0.002
		[1.40]		[1.35]
Auction term (days)		0.11***		0.09***
		[7.65]		[7.01]
ln(Auction size) (Bn.)		−0.21***		−0.12*
		[−2.91]		[−1.90]
Year-end		12.77***		3.39
		[6.26]		[1.28]
Ted spread (bps)		0.01**		0.01**
		[2.20]		[2.05]
Constant		7.44***		6.69***
		[4.51]		[4.32]
Auction FE	Yes	No	Yes	No
Banks	33	33	34	34
Auctions	166	175	170	175
Observations	975	984	1,045	1,050
Adjusted R^2	0.47	0.41	0.25	0.23

Table 3.8: Liquidity Uptake and Collateral Quality

The table reports results from a panel regression. In columns 1 and 2, the dependent variable is *Normalized Award*, and in columns 3 and 4, the dependent variable is *Normalized Demand*. Both of the variables are expressed in percentage points. Column 1 and 3 report results with auction fixed effects, and column 2 and 4 report results without. A detailed description of all variables is enclosed in Table A1 in the appendix. The t-stats reported in parenthesis are based on standard errors clustered at the bank level. The *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Normalized Award (%)		Normalized Demand (%)	
Haircut (%)	0.12**	0.12**	0.15**	0.14**
	[2.11]	[2.09]	[2.18]	[2.16]
Normalized reserves (%)	−0.01***	−0.004***	−0.01***	−0.004***
	[−3.79]	[−3.22]	[−3.88]	[−3.52]
ln(Assets) (Bn.)	−0.21***	−0.19***	−0.22***	−0.19***
	[−4.12]	[−3.53]	[−4.08]	[−3.74]
Equity ratio (%)	−0.11***	−0.07*	−0.12***	−0.08**
	[−2.97]	[−1.93]	[−2.90]	[−2.24]
Foreign bank	0.86*	1.06**	0.99**	1.16***
	[1.87]	[2.55]	[2.06]	[2.80]
Last auction participation	0.25***	0.18***	0.28***	0.22***
	[5.20]	[5.06]	[4.83]	[5.25]
Year-end		0.78		0.80***
		[1.42]		[2.92]
ln(Auction size) (Bn.)		0.30**		0.23**
		[2.16]		[2.39]
Overlapping auction		−0.11*		−0.16**
		[−1.80]		[−2.36]
Constant		3.66**		3.92***
		[2.73]		[3.18]
Auction FE	Yes	No	Yes	No
Banks	33	33	34	34
Auctions	166	175	170	175
Observations	975	984	1,045	1,050
Adjusted R^2	0.43	0.44	0.47	0.48

Figure 3.1: Development of Aggregate Reserves

The figure shows the development of aggregate banking reserves over the period from October 2011 to April 2016. The red dotted line represents the target level of banking reserves at NOK 35 bn. and the blue dotted line represents the aggregate amount of quotas at NOK 45 bn.

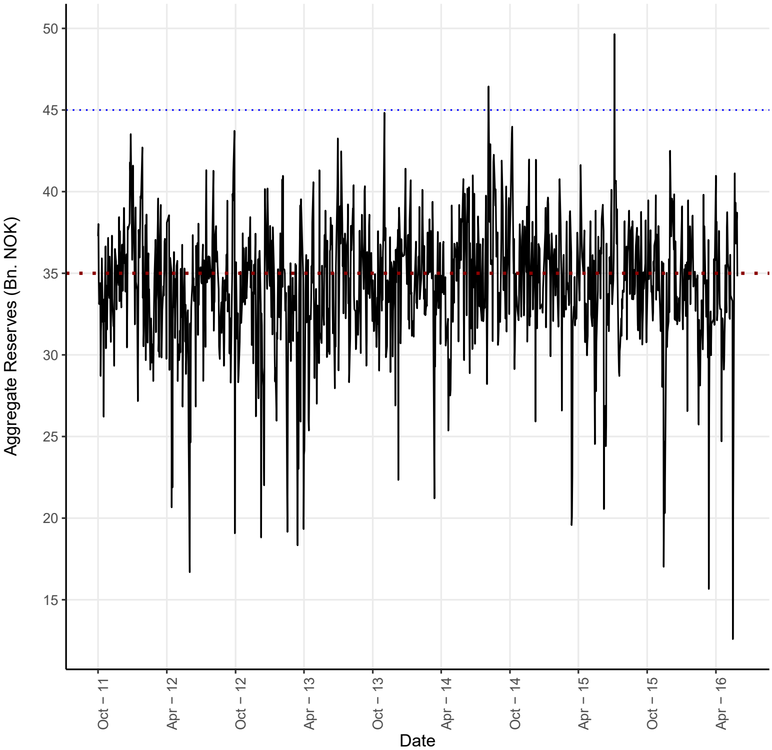


Figure 3.2: Auction Volume

The figure shows the annual amount of liquidity injected and withdrawn through Norges bank liquidity auctions over the period from October 2011 to April 2016. The liquidity-providing auctions are denoted as F-loan whereas the liquidity-draining auctions are denoted as F-deposit.

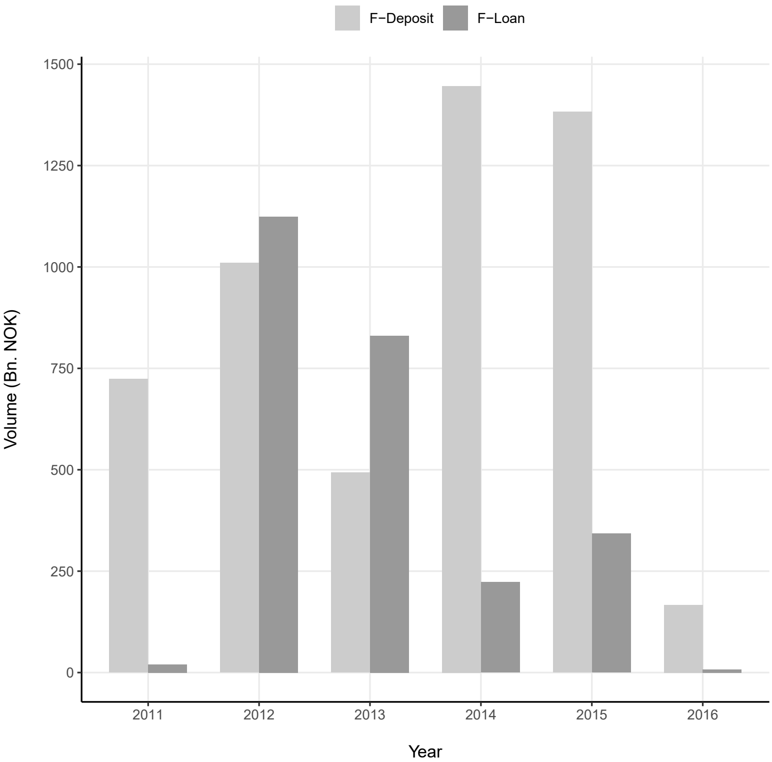


Figure 3.3: Development of Key Rates

The figure shows the development of key rates over the period from October 2011 to April 2016. The gray line denotes the marginal lending rate; the blue line depicts the policy rate of the Norges Bank; the green line represents the Norwegian overnight weighted average rate (NOWA); and the red line displays the reserve rate.

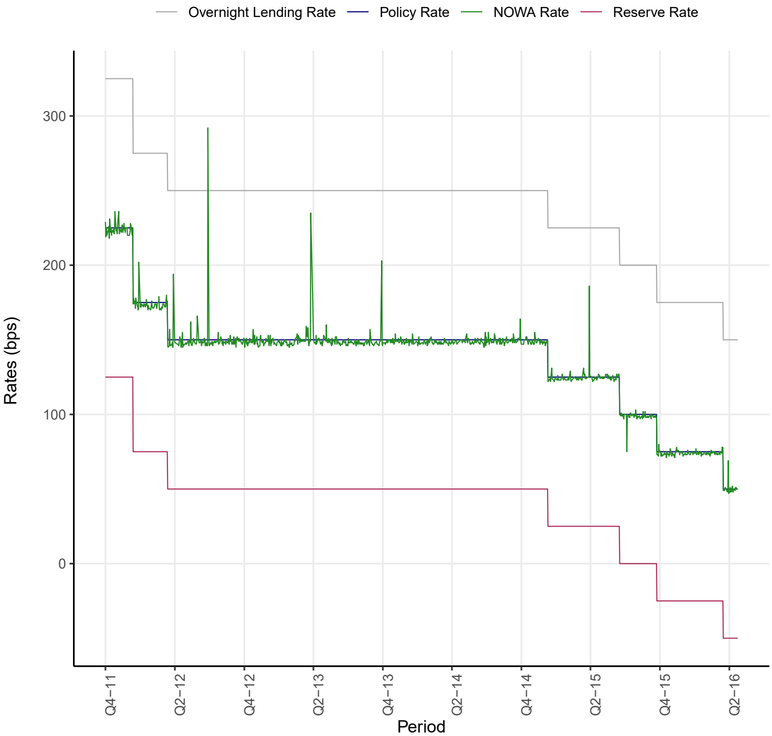
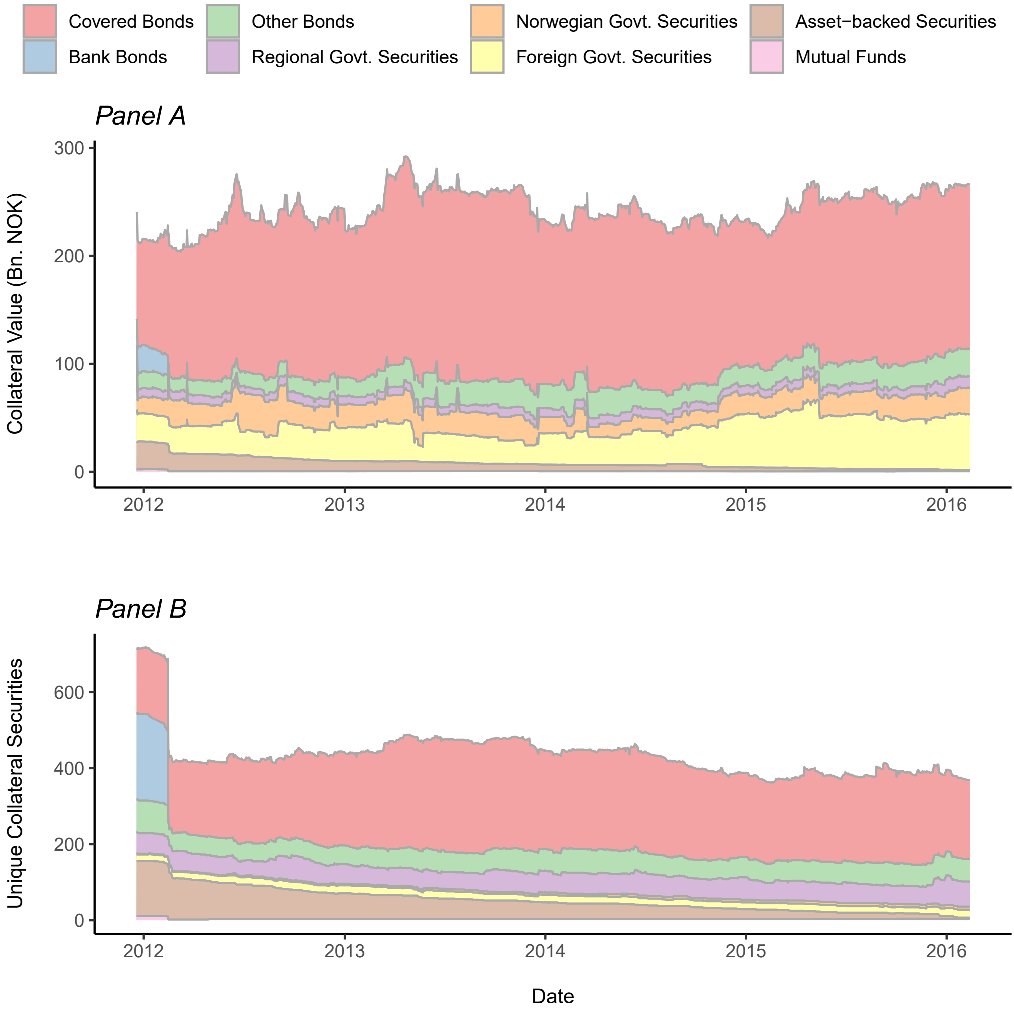


Figure 3.4: Composition of Pledged Collateral Pool

The figure shows the composition of pledged collateral at Norges Bank over the period from December 2011 to April 2016. Panel A illustrates the composition based on the haircut-adjusted value of collateral. Panel B depicts the composition based on the unique count of collateral securities. Other bonds include securities issued by non-financial corporations and supranational authorities.



3.A Additional Tables

Table A1: Variable Definitions

The table describes the variables used in the paper. The auction always refers to the F-loan auction.

Variable	**Definition**
Auction Variables	
Auction Size	Total liquidity allotted in an auction, expressed in NOK billion.
Bid Volume	Bid volume (either aggregate or bank-specific) in an auction, expressed in NOK billion.
Accepted Volume	Accepted bid volume of a bank in an auction, expressed in NOK billion.
Auction Term	Auction maturity expressed in days.
Number of Participants	Number of participating banks in an auction.
Bids	Number of bids submitted in an auction.
Overlapping Auction	Takes a value of one if the auction maturity coincides with another auction and zero otherwise.
Award ratio	Accepted bid volume (either aggregate or bank-specific) as a fraction of the corresponding submitted bid volume in an auction.
Coverage ratio	Bid volume of a bank in an auction as a fraction of its credit limit.
Premium	Difference in basis points between the volume-weighted average bid rate of the bank based on all submitted bids and the Norges Bank policy rate or the Norwegian overnight weighted average rate.
Overpricing	Difference in basis points between the volume-weighted average bid rate of the bank conditional on successful bids and the Norges Bank policy rate or the Norwegian overnight weighted average rate.
Normalized Demand	Bid volume of a bank in an auction as a percent of its assets or reserve quota.
Normalized Award	Accepted bid volume of a bank in an auction as a percent of its assets or reserve quota.
Participation Rate	Number of auctions that a bank participated in as a percent of all auctions held over the sample period.
Participation Last Auction	Takes a value of one if the bank participated in the previous auction and zero otherwise.
Year-end	Takes a value of one if the auction is held at the end of year and zero otherwise.

Continued on next page

Liquidity Variables	
Normalized Reserves	Start-of-day reserve balance (either aggregate or bank-specific) expressed as a percent of corresponding quotas.
Volatility Normalized Reserves	Standard deviation of the bank's normalized reserves over the previous 60 days.
Imbalance	Standard deviation of normalized reserves across all banks.
Reserve Quotas	The reserve quota of a bank expressed in NOK million.
Credit Limit	Available credit limit of a bank based on its haircut-adjusted collateral value net of any outstanding loans expressed in NOK billion.
NOWA Spread	Difference in basis points between the Norwegian weighted overnight rate and the contemporaneous policy rate of Norges Bank.
NOWA Volume	Daily trading volume in the Norwegian unsecured interbank market expressed in NOK billion.
Ted Spread	Difference in basis points between the three-month Norwegian interbank offered rate and the three-month Norwegian treasury bill yield.
Collateral Variables	
Haircut	Volume-weighted average haircut of a bank's pledged collateral, expressed in percent.
Haircut Dispersion	Standard deviation of the collateral haircut in the bank's eligible collateral stock.
Non-Pledged Haircut	The average haircut of eligible collateral securities which banks do not pledge with NB, expressed in percent.
Capacity	Complement of the ratio of a bank' pledged and eligible collateral stock, expressed in percent.
Match Ratio	Proportion of a bank's pledged collateral securities with Norges Bank that can be matched against its security holdings.
Foreign	Percent of foreign securities in a bank's eligible collateral portfolio.
Accounting Variables	
Assets	Bank's total assets expressed in NOK million.
ROE	Bank's return on equity expressed in percent.
Equity Ratio	Bank's book equity as a fraction of its assets, expressed in percent.

Continued on next page

Other Bank Variables	
Settlement Bank	Takes a value of one if the bank is a settlement bank and zero otherwise; Includes DNB and Sparebank SMN.
Foreign Bank	Takes a value of one if the bank is a foreign bank and zero otherwise.

Table A2: Comparison of Collateral Characteristics

The table compares the collateral characteristics of banks which participate at least once in F-loan auctions over the sample period and those that never participate in F-loan auctions. For each variable shown, I first calculate the time-series average at the bank-level and then report the cross-sectional statistics across all bidding and non-bidding banks separately. The *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Bidders			**Non-Bidders**			**Difference**
	Observations	Mean	SD	Observations	Mean	SD	
Haircut (%)	35	5.87	1.44	95	6.06	1.73	−0.12
Maturity (days)	35	1331.77	397.15	95	1194.96	324.93	136.08
Credit Rating (1 best)	35	1.48	0.46	95	1.69	1.38	−0.21
NOK Securities (%)	35	93.74	12.96	95	97.56	14.63	-3.82
Fixed-rate Securities (%)	35	9.60	12.24	95	5.28	17.46	4.32
Norwegian Treas. Securities (%)	35	4.09	16.83	95	2.55	12.15	1.54
Traded Securities (%)	35	44.58	16.27	95	49.41	18.29	−4.83
Own Securities (%)	35	1.05	3.74	95	0.57	4.94	0.48
HHI Collateral Category	35	0.66	0.16	95	0.82	0.15	-0.15^{***}

Table A3: Robustness - Liquidity Price and Collateral Quality Excluding DNB

The table reports results from a panel regression. In columns 1 and 2, the dependent variable is *Overpricing*, and in columns 3 and 4, the dependent variable is *Premium*. Both of the variables are expressed in basis points. Column 1 and 3 report results with auction fixed effects, and column 2 and 4 report results without. A detailed description of all variables is enclosed in Table A1. The t-stats reported in parenthesis are based on standard errors clustered at the bank level. The *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Overpricing (bps)		Premium (bps)	
Haircut (%)	0.05	0.04	0.02	0.02
	[0.99]	[0.72]	[0.33]	[0.24]
Normalized reserves (%)	-0.01^{**}	-0.004^{*}	-0.01^{**}	-0.004^{**}
	[−2.43]	[−1.94]	[−2.32]	[−2.11]
ln(Assets) (Bn.)	-0.48^{***}	-0.55^{***}	-0.45^{***}	-0.48^{***}
	[−3.33]	[−3.52]	[−2.82]	[−3.18]
ln(Bid volume) (Bn.)	0.33^{**}	0.41^{**}	0.36^{**}	0.38^{**}
	[2.22]	[2.32]	[2.28]	[2.33]
Participation rate (%)	-0.02^{***}	-0.02^{***}	-0.02^{***}	-0.02^{***}
	[−3.09]	[−3.52]	[−2.60]	[−2.99]
Imbalance (%)		0.003		0.003
		[1.53]		[1.55]
Auction term (days)		0.11^{***}		0.09^{***}
		[6.64]		[6.08]
ln(Auction size) (Bn.)		-0.21^{***}		-0.11^{*}
		[−2.79]		[−1.74]
Year-end		12.61^{***}		3.29
		[6.22]		[1.23]
Ted spread (bps)		0.01^{**}		0.01^{**}
		[2.27]		[2.10]
Constant		8.32^{***}		7.33^{***}
		[3.89]		[3.62]
Auction FE	Yes	No	Yes	No
Banks	32	32	33	33
Auctions	160	172	165	174
Observations	852	864	914	923
Adjusted R^2	0.44	0.38	0.21	0.19

Table A4: Robustness - Liquidity Uptake and Collateral Quality Excluding DNB

The table reports results from a panel regression. In columns 1 and 2, the dependent variable is *Normalized Award*, and in columns 3 and 4, the dependent variable is *Normalized Demand*. Both of the variables are expressed in percentage points. Column 1 and 3 report results with auction fixed effects, and column 2 and 4 report results without. A detailed description of all variables is enclosed in Table A1. The t-stats reported in parenthesis are based on standard errors clustered at the bank level. The *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Normalized Award (%)		Normalized Demand (%)	
Haircut (%)	0.18***	0.18***	0.21***	0.20***
	[3.10]	[3.41]	[3.17]	[3.37]
Normalized reserves (%)	−0.01***	−0.01***	−0.01***	−0.01***
	[−4.22]	[−3.89]	[−4.45]	[−4.34]
ln(Assets) (Bn.)	−0.14***	−0.12**	−0.13***	−0.12**
	[−3.10]	[−2.10]	[−3.00]	[−2.29]
Equity ratio (%)	−0.10**	−0.06	−0.10**	−0.07
	[−2.14]	[−1.29]	[−1.99]	[−1.51]
Foreign bank	0.77	0.95**	0.90*	1.05**
	[1.61]	[2.28]	[1.81]	[2.48]
Last auction participation	0.28***	0.21***	0.32***	0.24***
	[5.92]	[5.85]	[5.57]	[5.54]
Year-end		0.86		0.83***
		[1.42]		[2.90]
ln(Auction size) (Bn.)		0.28*		0.20**
		[1.88]		[1.98]
Overlapping auction		−0.16**		−0.21***
		[−2.45]		[−2.91]
Constant		2.24		2.40*
		[1.43]		[1.71]
Auction FE	Yes	No	Yes	No
Banks	32	32	33	33
Auctions	160	172	165	174
Observations	852	864	914	923
Adjusted R^2	0.43	0.43	0.48	0.48

Bibliography

Åberg, P., Corsi, M., Grossmann-Wirth, V., Hudepohl, T., Mudde, Y., Rosolin, T., and Schobert, F. (2021). Demand for central bank reserves and monetary policy implementation frameworks: the case of the eurosystem. *ECB occasional paper*, (2021/282).

Adrian, T., Boyarchenko, N., and Shachar, O. (2017). Dealer balance sheets and bond liquidity provision. *Journal of Monetary Economics*, 89:92–109.

An, Y. (2020). Competing with inventory in dealership markets. Working paper.

Avalos, F. and Xia, D. (2021). Investor size, liquidity and prime money market fund stress. *BIS Quarterly Report*.

Baba, N., McCauley, R. N., and Ramaswamy, S. (2009). Us dollar money market funds and non-us banks. *BIS Quarterly Review*.

Babus, A. and Kondor, P. (2018). Trading and information diffusion in over-the-counter markets. *Econometrica*, 86(5):1727–1769.

Baghai, R. P., Giannetti, M., and Jäger, I. (2022). Liability structure and risk taking: Evidence from the money market fund industry. *Journal of Financial and Quantitative Analysis*, 57(5):1771–1804.

Bao, J., O'Hara, M., and Zhou, X. A. (2018). The volcker rule and corporate bond market making in times of stress. *Journal of Financial Economics*, 130(1):95–113.

Bechtel, A., Eisenschmidt, J., Ranaldo, A., and Veghazy, A. V. (2021). Quantitative easing and the safe asset illusion. *Working Paper*.

Becker, B. and Ivashina, V. (2015). Reaching for yield in the bond market. *The Journal of Finance*, 70(5):1863–1901.

Bessembinder, H., Jacobsen, S., Maxwell, W., and Venkataraman, K. (2018). Capital commitment and illiquidity in corporate bonds. *The Journal of Finance*, 73(4):1615–1661.

Bindseil, U., Corsi, M., Sahel, B., and Visser, A. (2017). The eurosystem collateral framework explained. *Occasional Paper Series. European Central Bank*, (189).

Bouveret, A., Schaanning, E., and Baes, M. (2021). Regulatory constraints for money market funds: The impossible trinity? *Available at SSRN*.

Brady, S., Anadu, K., and Cooper, N. (2012). The stability of prime money market mutual funds: sponsor support from 2007 to 2011. *Federal Reserve Bank of Boston*.

Bretscher, L., Schmid, L., and Ye, T. (2023). Passive demand and active supply: Evidence from maturity-mandated corporate bond funds. Working paper.

Caballero, R. J., Farhi, E., and Gourinchas, P.-O. (2017). The safe assets shortage conundrum. *Journal of Economic Perspectives*, 31(3):29–46.

Casavecchia, L., Ge, G., Li, C., and Tiwari, A. (2020). Prime time for prime funds: Floating nav, intraday redemptions and liquidity risk during crises. *Working Paper*.

Chakravarty, S. and Sarkar, A. (2003). Trading costs in three U.S. bond markets. *The Journal of Fixed Income*, 13(1):39–48.

Chernenko, S. and Sunderam, A. (2014). Frictions in shadow banking: Evidence from the lending behavior of money market mutual funds. *The Review of Financial Studies*, 27(6):1717–1750.

Choi, D. B., Santos, J. A., and Yorulmazer, T. (2021). A theory of collateral for the lender of last resort. *Review of Finance*, 25(4):973–996.

Choi, J., Huh, Y., and Shin, S. S. (2022). Customer liquidity provision: Implications for corporate bond transaction costs. *Forthcoming, Management Science*.

Cipriani, M. and La Spada, G. (2020). Sophisticated and unsophisticated runs. *FRB of New York Staff Report No. 956*.

Cipriani, M. and La Spada, G. (2021). Investors' appetite for money-like assets: The mmf industry after the 2014 regulatory reform. *Journal of Financial Economics*, 140(1):250–269.

Colliard, J.-E., Foucault, T., and Hoffmann, P. (2021). Inventory management, dealers' connections, and prices in over-the-counter markets. *The Journal of Finance*, 76(5):2199–2247.

Council of European Union (2017). Regulation (eu) 2017/1131 of the european parliament and of the council of 14 june 2017 on money market funds.

De Roure, C. and McLaren, N. (2021). Liquidity transformation, collateral assets and counterparties. *Central Bank Review*, 21(4):119–129.

Delatte, A.-L., Garg, P., and Imbs, J. (2024). The real effects of the bank lending channel of monetary policy. *Working Paper*.

Di Maggio, M., Kermani, A., and Song, Z. (2017). The value of trading relations in turbulent times. *Journal of Financial Economics*, 124(2):266–284.

Dick-Nielsen, J. and Poulsen, T. K. (2019). How to clean academic trace data. Working paper.

Dick-Nielsen, J. and Rossi, M. (2019). The Cost of Immediacy for Corporate Bonds. *The Review of Financial Studies*, 32(1):1–41.

Drechsler, I., Drechsel, T., Marques-Ibanez, D., and Schnabl, P. (2016). Who borrows from the lender of last resort? *The Journal of Finance*, 71(5):1933–1974.

Duffie, D., Scheicher, M., and Vuillemey, G. (2015). Central clearing and collateral demand. *Journal of Financial Economics*, 116(2):237–256.

Dunne, P. G. and Giuliana, R. (2021). Do liquidity limits amplify money market fund redemptions during the covid crisis? *ESRB: Working Paper No. 127*.

Edwards, A. K., Harris, L. E., and Piwowar, M. S. (2007). Corporate bond market transaction costs and transparency. *Journal of Finance*, 62(3):1421–1451.

European Central Bank (2022). ECB announces timeline to phase out temporary pandemic collateral easing measures. Retrieved from `https://www.ecb.europa.eu/press/pr/date/2022/html/ecb.pr220324~8b7f2ff5ea.en.html`.

European Fund and Asset Management Association (2020). European mmfs in the covid-19 market turmoil: Evidence, experience and tentative considerations around eventual future reforms.

Fang, H., Wang, Y., and Wu, X. (2020). The collateral channel of monetary policy: Evidence from china. *National Bureau of Economic Research*, (26792).

Fecht, F., Nyborg, K. G., and Rocholl, J. (2011). The price of liquidity: The effects of market conditions and bank characteristics. *Journal of Financial Economics*, 102(2):344–362.

Fecht, F., Nyborg, K. G., Rocholl, J., and Woschitz, J. (2016). Collateral, central bank repos, and systemic arbitrage. *Swiss Finance Institute Research Paper*, (16-66).

Feldhütter, P. (2012). The same bond at different prices: Identifying search frictions and selling pressures. *Review of Financial Studies*, 25(4):1115–1206.

Financial Stability Board (2020). Global monitoring report on non-bank financial intermediation.

Fisch, J. E. (2018). The broken buck stops here: Embracing sponsor support in money market fund reform. *Journal of Financial Perspectives*, 5(1).

Fitch Ratings (2021). Money market fund rating criteria.

Fornasari, F. (2018). De-moneynising mmf shares: Third party support in the united states and the european union. *NYU Journal of International Law and Politics*, 51(1):1313.

Friewald, N. and Nagler, F. (2019). Over-the-counter market frictions and yield spread changes. *The Journal of Finance*, 74(6):3217–3257.

Gallagher, E. A., Schmidt, L. D., Timmermann, A., and Wermers, R. (2020). Investor information acquisition and money market fund risk rebalancing during the 2011–2012 eurozone crisis. *The Review of Financial Studies*, 33(4):1445–1483.

Goldstein, M. A. and Hotchkiss, E. S. (2020). Providing liquidity in an illiquid market: Dealer behavior in us corporate bonds. *Journal of Financial Economics*, 135(1):16–40.

Gorton, G., Laarits, T., and Muir, T. (2022). Mobile collateral versus immobile collateral. *Journal of Money, Credit and Banking*, 54(6):1673–1703.

Green, R. C., Hollifield, B., and Schürhoff, N. (2007). Financial intermediation and the costs of trading in an opaque market. *The Review of Financial Studies*, 20(2):275–314.

Hasbrouck, J. and Levich, R. M. (2021). Network structure and pricing in the fx market. *Journal of Financial Economics*, 141(2):705–729.

Hollifield, B., Neklyudov, A., and Spatt, C. (2017). Bid-ask spreads, trading networks, and the pricing of securitizations. *The Review of Financial Studies*, 30(9):3048–3085.

Hollifield, B., Neklyudov, A., and Spatt, C. (2020). Volume and intermediation in corporate bond markets. Working paper.

Huang, L. and Wei, B. (2017). Inventory risk and dealer competition in a dealer network. Working paper.

Hugonnier, J., Lester, B. R., and Weill, P.-O. (2020). Frictional intermediation in over-the-counter markets. *The Review of Economic Studies*, 87(3):1432–1469.

Hüttl, P. and Kaldorf, M. (2024). The transmission of bank liquidity shocks: Evidence from the eurosystem collateral framework. *Deutsche Bundesbank Discussion Paper*, (04/2024).

Jacewitz, S., Unal, H., and Wu, C. (2021). Shadow insurance? money market fund investors and bank sponsorship. *KC FED Research Working Paper*.

Jasova, M., Laeven, L., Mendicino, C., Peydró, J.-L., and Supera, D. (2023). Systemic risk and monetary policy: The haircut gap channel of the lender of last resort. *The Review of Financial Studies*, page hhad100.

Kacperczyk, M. and Schnabl, P. (2013). How safe are money market funds? *The Quarterly Journal of Economics*, 128(3):1073–1122.

Kyle, A. S. (1989). Informed speculation with imperfect competition. *The Review of Economic Studies*, 56(3):317–355.

Li, D. and Schürhoff, N. (2019). Dealer networks. *The Journal of Finance*, 74(1):91–144.

Li, L., Li, Y., Macchiavelli, M., and Zhou, X. (2021). Liquidity Restrictions, Runs, and Central Bank Interventions: Evidence from Money Market Funds. *The Review of Financial Studies*, 34(11):5402–5437.

Li, W. and Song, Z. (2019). Dealers as information intermediaries in over-the-counter markets. Working paper.

Li, W. and Song, Z. (2020). Dealer expertise and market concentration in otc trading. Working paper.

Madhavan, A. and Smidt, S. (1993). An analysis of changes in specialist inventories and quotations. *The Journal of Finance*, 48(5):1595–1628.

McCabe, P. (2010). The cross section of money market fund risks and financial crises. Working paper. *Federal Reserve Board*.

Mésonnier, J.-s., O'DONNELL, C., and Toutain, O. (2022). The interest of being eligible. *Journal of Money, Credit and Banking*, 54(2-3):425–458.

Moody's Investor Services (2010). Sponsor support key to money market funds.

Neklyudov, A. (2019). Bid-ask spreads and the over-the-counter interdealer markets: Core and peripheral dealers. *Review of Economic Dynamics*, 33:57–84.

Norges Bank (2013). Financial stability report. Technical report, Norges Bank.

Nyborg, K. G. (2016). Collateral frameworks. *Cambridge Books*.

Nyborg, K. G. (2017). Central bank collateral frameworks. *Journal of Banking & Finance*, 83:232–248.

Ottonello, G. (2019). The impact of benchmarking in fixed income markets. Working paper.

Parlatore, C. (2016). Fragility in money market funds: Sponsor support and regulation. *Journal of Financial Economics*, 121(3):595–623.

Pelizzon, L., Riedel, M., Simon, Z., and Subrahmanyam, M. G. (2024). Collateral eligibility of corporate debt in the eurosystem. *Journal of Financial Economics*, 153:103777.

President's Working Group on Financial Markets (2020). Overview of recent events and potential reform options for money market funds. `https://home.treasury.gov/system/files/136/PWG-MMF-report-final-Dec-2020.pdf`.

Sambalaibat, B. (2022). Endogenous specialization and dealer networks. Working paper.

Schmidt, L., Timmermann, A., and Wermers, R. (2016). Runs on money market mutual funds. *American Economic Review*, 106(9):2625–2657.

Schultz, P. (2001). Corporate bond trading costs: A peek behind the curtain. *The Journal of Finance*, 56(2):677–698.

Schultz, P. (2017). Inventory management by corporate bond dealers. Working paper.

Securities and Exchange Commission (2014). Money market fund reform; amendments to form pf, Release no. 33-9616. `https://www.sec.gov/files/rules/final/2014/33-9616.pdf`.

Shen, J., Wei, B., and Yan, H. (2020). Financial intermediation chains in an over-the-counter market. *Management Science*, 67(7):4623–4642.

Ueda, K. and Di Mauro, B. W. (2013). Quantifying structural subsidy values for systemically important financial institutions. *Journal of Banking & Finance*, 37(10):3830–3842.

Van Bekkum, S., Gabarro, M., and Irani, R. M. (2018). Does a larger menu increase appetite? collateral eligibility and credit supply. *The Review of Financial Studies*, 31(3):943–979.

Vives, X. (2011). Strategic supply function competition with private information. *Econometrica*, 79(6):1919–1966.

Wang, C. (2018). Core-periphery trading networks. Working paper.

Witmer, J. (2019). Strategic complementarities and money market fund liquidity management. *Journal of Financial Intermediation*, 38:58–68.

Üslü, S. (2019). Pricing and liquidity in decentralized asset markets. *Econometrica*, 87(6):2079–2140.

Series of Dissertations

2024

4/2024 *Obaidur Rehman*
Essays in Empirical Market Microstructure

3/2024 *Andrew Sang Jun Rhee*
Social, Biological and Cultural Foundations of Corporate and Investor Behaviors

2/2024 *Anna Stepanova*
When Should Organizations Outsource Problem-Solving?
Balancing Functional and Technical Requirement Specifications in Public Procurement

1/2024 *Audun Reiby*
Cognitive Distance, Network Embeddedness, and the Performance of Alliance Partners
A Conceptual and Empirical Approach

2023

16/2023 *Katarzyna M. Adamska*
Mindsets In Organizations – How Fixed and Growth Beliefs Influences Employee Outcomes

15/2023 *Thomas McKay*
Essays about Auctions and Bargaining:
Theory and Experiments

14/2023 *Oda Nedregård*
The party is on, get in line:
Essays on the political economy of party discipline.

13/2023 *Tohid Ghanbarpour*
Doing Good and Doing Well:
Creating Value Through Corporate Social Responsibility

12/2023 *Lewend Mayiwar*
Emotion Regulation via Self-Distancing:
Consequences for Risk-Taking and Cognitive Processing

11/2023 *Farhana Tabassum*
How Repetition-Induced Learning Influences Consumers' Perceptions

10/2023 *Morten Grindaker*
Empirical Essays in Labor Economics and Housing Search

9/2023 *Linnea Lorentzen*
Trade and Worker Reallocation

8/2023 *Tine Malonæs*
Creating room for innovation
A business history study of innovation in the
Kongsberg Group, 2000 – 2015

7/2023 *Jon Ellingsen*
Essays in prediction, expectaion formation, and labor economics

6/2023 *Felix Kapfhammer*
The Macroeconomic Consequences of the Green Transition

5/2023 *Bryndís Dögg Steindórsdóttir*
Opportunities and Obstacles to Career Success: A Lifespan Developmental Perspective

4/2023 *Ivan Korsak*
On the Structure and Evolution of Marketing Science

3/2023 *Vasyl Kotsovskyi*
Three essays in portfolio management

2/2023 *Jonas Hveding Hamang*
Essay on the determinants of oil, and the post-oil era and democracy

1/2023 *Binh Minh Thi Truong*
How Does an Acquisition Affect a Firm's Alliance?

2022
6/2022 *Olga Ungureanu*
Marketing Communications for New Product Launches: A Multiple Stakeholder Perspective

5/2022 *Sverre S Ubisch*
Essays on Positioning, Categorization, and Performance

4/2022 *Magnus A. H. Gulbrandsen*
Essays in Household Finance and Macroeconomics

3/2022 *Christian Winther Farstad*
Leaders for art's sake? Potentials and requirements for developing cross-functional leadership in the field of art

2/2022 *Ingvild Andersen*
Reconnecting Leader-Member Exchange and Social Exchange Theory

1/2022 *Thomas S. Gundersen*
Supply Heterogeneities and the Oil Market

2021
11/2021 *Espen Christopher Skretting*
Firms, Oil and Stocks

10/2021 *Marius Andersson*
Texts and texturing in and around organizations: A discursive perspective on temporal work, future constructions, and managers' latitude of action

9/2021 *Gilbert Kofi Adarkwah*
Institutions, Policy Risk, and Firms Behavior: Foreign Investments in High-Risk Countries

8/2021 *Ilka Verena Ohlmer*
The Social Side of Employee Pay: Exploring social-psychological outcomes and the explanatory mechanisms of employee pay standing from the social-effects perspective on pay

7/2021 *Emanuela Stagno*
Some Consequences of Vulnerability in Consumers' Life

6/2021 *Christopher Albert Sabel*
Spinouts, Sharks, and Genealogy: Established Firms as Resource Acquisition Channel for Startups

5/2021 *Njål Andersen*
No article is an island entire of itself: Extending bibliometric science mapping in the field of management with social network analysis

4/2021 *Julia Zhulanova*
Macroeconomic Dynamics, Commodity Prices and Expectations

3/2021 *Magnus Våge Knutsen*
Essays on reputation

2/2021 *Even Comfort Hvinden*
CRUDE GAMES: Essays on strategic competition in oil markets

1/2021 *Namhee Matheson*
Theory and Evidence on the Effect of Disagreement on Asset Prices

2020

7/2020 *Rasmus Bøgh Holmen*
Productivity and Mobility

6/2020 *Arne Fredrik Lyshol*
Essays in labor and housing search

5/2020 *Irena Kustec*
Three essays on family firms

4/2020 *Kateryna Maltseva*
Digital Self-Tracking: Psychological and Behaviroal Implications

3/2020 *Flladina Zilja*
The role of CEOs in international strategy

2/2020 *Vedrana Jez*
Managerial Attention and Cognitive Flexibility in Strategic Decision Making

1/2020 *Ling Tak Douglas Chung*
Three Essays on Retail Trading

2019

7/2019 *Adeline Holmedahl Hvidsten*
The role of incompleteness in co-designing collaborative service delivery: A case study of electronic coordination in Norwegian health care

6/2019 *Delphine Caruelle*
The Interplay between Time and Customer Emotion during Service Encounters

5/2019 *Chi Hoang*
How the Human Schema Guides Consumer Behavior

4/2019 *Wah Yip Chu*
Essays in Empirical Asset Pricing and Investment

3/2019 *Olga Mikhailova*
Medical technological innovation processes: The role of inter-relatedness at the global and local levels for the case Transcatheter of Aortic Valve Implantation

2/2019 *Jo Albertsen Saakvitne*
Essays on Market Microstructure

1/2019 *Per-Magnus Moe Thompson*
All you need is love?: Investigating leadership from leaders' attachment experiences in close relationships

2018

15/2018 *Stefania Sardo*
Questioning normality: A study of obduracy and innovation in the O&G industry

14/2018 *Ingvild Müller Seljeseth*
The Inevitable Thucydides's Trap?: How Hierarchical Instability and Threat Influences Leaders' Openness to Inputs from Others

13/2018 *Daniela Carmen Cristian*
The Utility of Hedonics Beyond Pleasure: Positive Outcomes of Hedonic Consumption

12/2018 *Daniel Øgård Kinn*
Essays in Econometrics

11/2018 *Ragnar Enger Juelsrud*
Essays in Macro-Finance

10/2018 *Bisrat Agegnehu Misganaw*
On entrepreneurial teams and their formation in science-based industries

9/2018 *Martin Blomhoff Holm*
Consumption

8/2018 *Helene Lie Røhr*
Essays on decision making dynamics in politics and consumer choice

7/2018 *Hoang Ho*
Are Human Resource Management (HRM) Systems Good or Bad for Employee Well-Being?: An Investigation of the Well-being Paradox from the Mutual Gains and Critical Perspectives

6/2018 *Rannveig Røste*
Innovation in Public Services: Wicked Problems and Multi-layered Solutions

5/2018 *Mathias Hansson*
The Complex Simplicity of Patterns of Action: Organizational Routines as Source of Adaptation and Performance

4/2018 *Mariia Koval*
Antecedents and Consequences of Unplanned Alliance Terminations

3/2018 *Maximilian Rohrer*
Three Essays in Financial Economics

2/2018 *Viacheslav Iurkov*
The role of alliance networks for firms' geographic scope and performance: A structural embeddedness perspective

1/2018 *Huy-Vu Nguyen*
Wealth Inequality

2017

14/2017 *Mirha Suangic*
Aspirations and Daring Confrontations: Investigating the Relationship between Employees' Aspirational Role-Identities and Problem-Oriented Voice

13/2017 *Beniamino Callegari*
A heterodox theoretical interpretation

12/2017 *Sepideh Khayati Zahiri*
Essays on Predictive Ability of Macroeconomic Variables and Commodity Prices

11/2017 *Tonje Hungnes*
Reorganizing healthcare services: Sensemaking and organizing innovation

10/2017 *Eileen Fugelsnes*
From backstage to consensus: A study of the Norwegian pension reform process

9/2017 *Knut-Eric Neset Joslin*
Experimental Markets with Frictions

8/2017 *Sumaya AlBalooshi*
Switching between Resources: Psychosocial Resources as Moderators of the Impact of Powerlessness on Cognition and Behavior

7/2017 *Zongwei Lu*
Three essays on auction theory and contest theory

6/2017 *Frode Martin Nordvik*
Oil Extraction and The Macroeconomy

5/2017 *Elizabeth Solberg*
Adapting to Changing Job Demands: A Broadcast Approach to Understanding Self-Regulated Adaptive Performance and Cultivating it in Situated Work Settings

4/2017 *Natalia Bodrug*
Essays on economic choices and cultural values

3/2017 *Vegard Høghaug Larsen*
Drivers of the business cycle: Oil, news and uncertainty

2/2017 *Nikolay Georgiev*
Use of Word Categories with Psychological Relevance Predicts Prominence in Online Social Networks

1/2017 *Sigmund Valaker*
Breakdown of Team Cognition and Team Performance: Examining the influence of media and overconfidence on mutual understanding, shared situation awareness and contextualization

2016

12/2016 *Xiaobei Wang*
Strategizing in Logistics Networks: The role of Logistics Service Providers as mediators and network facilitators

11/2016 *Prosper Ameh Kwei-Narh*
A mid-range theory of monitoring behaviors, shared task mental models, and team performance within dynamic settings

10/2016 *Anton Diachenko*
Ownership type, performance, and context: Study of institutional and industrial owners

9/2016 *Ranvir S. Rai*
Innovation in Practice: A Practice-Theoretical Exploration of Discontinuous Service Innovations

8/2016 *Gordana Abramovic*
Effective Diversity Management on the Line - Who and How? On the role of line managers in organisations with a diverse workforce

7/2016 *Mohammad Ejaz*
Why do some service innovations succeed while others fail? A comparative case study of managing innovation processes of two internet-based aggregation financial services at Finn.no (Penger.no)

6/2016 *Asmund Rygh*
Corporate governance and international business: Essays on multinational enterprises, ownership, finance and institutions

5/2016 *Chen Qu*
Three Essays on Game Theory and Patent-Pool Formation

4/2016 *Arash Aloosh*
Three Essays in International Finance

3/2016 *John-Erik Mathisen*
Elaborating and Implemental Mindsets in Business-related Behavior: An Investigation of the Interface between Cognition and Action. How goals and plans emerge and relate to cognition and action in business.

2/2016 *Øyvind Nilsen Aas*
Essays in industrial organization and search theory

1/2016 *Dominque Kost*
Understanding Transactive Memory Systems in Virtual Teams: The role of integration and differentiation, task dependencies and routines

2015

8/2015 *Andreea Mitrache*
Macroeconomic Factors and Asset Prices – An Empirical Investigation

7/2015 *Lene Pettersen*
Working in Tandem: A Longitudinal Study of the Interplay of Working Practices and Social Enterprise Platforms in the Multinational Workplace

6/2015 *Di Cui*
Three Essays on Investor Recognition and Mergers & Acquisitions

5/2015 *Katja Maria Hydle*
Cross border practices: Transnational Practices in Professional Service Firms

4/2015 *Ieva Martinkenaitė-Pujanauskienė*
Evolutionary and power perspectives on headquarters-subsidiary knowledge transfer: The role of disseminative and absorptive capacities

3/2015 *Tarje Gaustad*
The Perils of Self-Brand Connections: Consumer Response to Changes in Brand Image

2/2015 *Jakob Utgård*
Organizational form, local market structure and corporate social performance in retail

1/2015 *Drago Bergholt*
Shocks and Transmission Channels in Multi-Sector Small Open Economies

2014

13/2014 *Nam Huong Dau*
Asset Pricing with Heterogeneous Beliefs and Portfolio Constraints

12/2014 *Vegard Kolbjørnsrud*
On governance in collaborative communities

11/2014 *Ignacio García de Olalla López*
Essays in Corporate Finance

10/2014 *Sebastiano Lombardo*
Client-consultant interaction practices: Sources of ingenuity, value creation and strategizing

9/2014 *Leif Anders Thorsrud*
International business cycles and oil market dynamics

8/2014 *Ide Katrine Birkeland*
Fire Walk with Me: Exploring the Role of Harmonious and Obsessive Passion in Well-being and Performance at Work

7/2014 Sinem Acar-Burkay
Essays on relational outcomes in mixed-motive situations

6/2014 Susanne H.G. Poulsson
On Experiences as Economic Offerings

5/2014 Eric Lawrence Wiik
Functional Method as a Heuristic and Research Perspective: A Study in Systems Theory

4/2014 Christian Enger Gimsø
Narcissus and Leadership Potential - The measurement and implications of narcissism in leadership selection processes

3/2014 Mehrad Moeini-Jazani
When Power Has Its Pants Down: Social Power Increases Sensitivity to Internal Desires

2/2014 Yuriy Zhovtobryukh
The role of technology, ownership and origin in M&A performance

1/2014 Siv Staubo
Regulation and Corporate Board Composition