Essays in Financial Stability and Intermediation

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by

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Petros Katsoulis

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This thesis is dedicated to my family

ABSTRACT

This thesis empirically examines the contribution of financial institutions to systemic risk by looking at their interactions with market-based finance. The financial crisis of 2007-09 catalysed the transformation of the financial system with the introduction of the post-crisis regulations, which were aimed at mitigating systemic risk by addressing vulnerabilities that manifested in the crisis. This resulted in the increased resilience of the banking sector, which was at the centre of the financial crisis, as well as the proliferation of market-based finance as an alternative source of funding for corporations. Yet, as the recent market turmoil due to Covid-19 has showcased, this has created new vulnerabilities which necessitate the continuous assessment of the evolving financial system.

The thesis is based on three essays. The first essay examines the effects of the mandatory collateralisation of over-the-counter derivatives contracts on counterparty, liquidity and systemic risks of the largest dealer banks and central counterparties (CCPs). Using a stress test network model calibrated to the banks' balance sheet data, we document risk-shifting effects in the form of risk transformation from counterparty to liquidity risk and a reduction of systemic risk at the expense of increased propensity for contagion from the CCP to its members. In addition, we find that the expansion of central clearing reduces systemic risk, in accordance with regulatory predictions.

The second essay examines the effects of exchange-traded funds (ETFs) on the underlying securities' liquidity, returns and volatility via information links which are formed when investors use information from one asset to price the other. Using a proprietary dataset of Irish ETF holdings from the Central Bank of Ireland, we find that ETFs form close information links with the underlying equities but weak ones with the underlying corporate debt securities because of the higher accessibility of the former, leading to stronger co-movements of liquidity, returns and volatility with the equities compared to the corporate debt securities. The results indicate that ETFs can affect the underlying markets in different ways depending on their accessibility, contributing to the ongoing

debate on the role of ETFs in propagating shocks and systemic risk.

Finally, the third essay examines the resilience of banks to liquidity shocks originating from money market funds (MMFs) using a stress test network model calibrated to the full US MMF holdings data, following the introduction of post-crisis regulations in both sectors. My findings suggest that while the banks can withstand a withdrawal of short-term funding from MMFs due to their high liquidity reserves, the MMFs can incur severe fire sales losses in the face of large redemption shocks and in the absence of a regulatory authority acting as buyer of last resort of commercial paper, despite the regulations introduced to increase their resilience.

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List of Abbreviations

ABCP asset-backed commercial paper

AP authorised participant

BCBS Basel Committee on Banking Supervision

BIS Bank for International Settlements

BoE Bank of England

bp basis point

CAR capital adequacy ratio

CBI Central Bank of Ireland

CCP central counterparty

CD certificate of deposit

CDS credit default swap

CFTC Commodity Futures Trading Commission

CM clearing member

CNAV constant net asset value

CP commercial paper

CPSS Committee on Payment and Settlement Systems

DF default fund

DLA daily liquid assets

DMP default management process

EMIR European Market Infrastructure Regulation

ESMA European Securities and Markets Authority

ESRB European Systemic Risk Board

ETF exchange-traded fund

FCA Financial Conduct Authority

FIA Futures Industry Association

FOC first order condition

FSB Financial Stability Board

G20 Group of Twenty

HQLA high-quality liquid assets

ICI Investment Company Institute

IM initial margin

IMF International Monetary Fund

IOSCO International Organization of Securities Commissions

IPV independent private value

ISDA International Swaps and Derivatives Association

LCR liquidity coverage ratio

MAGD Macroeconomic Assessment Group on Derivatives

MBF market-based finance

MM money market

MMF money market fund

NAV net asset value

NCC non-central clearing

OTC over-the-counter

RE real estate

RPF Reserve Primary Fund

SEC Securities and Exchange Commission

SNAV shadow net asset value

TD time deposit

TNA total net assets

VaR value-at-risk

VM variation margin

VMGH variation margin gains haircut

VNAV variable net asset value

WLA weekly liquid assets

Chapter 1

Introduction

1.1 Introduction

The financial crisis of 2007-09 revealed many of the vulnerabilities of the financial system and shortcomings of the existing regulatory framework at the time. The banking sector coexisted alongside a shadow banking sector that provided credit intermediation through a long chain of intermediaries without appropriate regulatory oversight. These intermediaries engaged in maturity and liquidity transformation by obtaining short-term funding and investing in less liquid longer-term assets using leverage, and transferred counterparty risk to other investors. By not being subject to bank regulations, shadow banks such as broker-dealers were not eligible for emergency borrowing from the central banks' discount window and they facilitated the housing market boom by securitising mortgage loans (often of low credit quality) and selling them to other investors. Importantly, the two sectors were closely interconnected as many shadow banking entities were owned by banks to reduce the latter's regulatory capital requirements while maintaining exposure to the activities of the former (Acharya et al., 2013), and as such they benefited from the sponsor banks' implicit support due to reputational reasons. At the same time, entities such as money market funds (MMFs) provided funding to the banking sector by investing in short-term debt such as commercial paper.

When the crisis hit, the banking sector was undercapitalised as a result of these unregulated activities and had no minimum liquidity requirements, leading to a global recession when it was unable to continue extending credit to the real economy after facing losses and a dry-up of funding (Cornett et al. (2011), Acharya and Mora (2015)). The shadow banking sector was also a key transmitter of stress. Market participants engaged in bilateral over-the-counter (OTC) derivatives trades that were often under- or uncollateralised, creating a complex web of exposures and fostering systemic risk. MMFs investing in short-term corporate debt experienced runs due to their structural vulnerabilities incentivising investors to withdraw their funds before others, reducing lending and exacerbating the funding problems of the financial sector while forcing sponsor banks to absorb the losses according to the International Monetary Fund (IMF) (IMF, 2010).

These events led to a rethinking of the regulatory framework that governs banks and other financial institutions, and the emergence of macroprudential regulation that aims to reduce systemic risk. Reforms were focused on strengthening the banks' capital and liquidity reserves via the introduction of Basel III as well as the resilience of shadow banking entities such as MMFs, and on redesigning the functioning of financial markets such as OTC derivatives via the mandatory clearing through central counterparties (CCPs) and the collateralisation of non-centrally cleared trades as mandated by the Group of Twenty (G20) (G20, 2009).

Today, most of these reforms have been fully implemented or are being finalised. The finalised Basel III framework (also called Basel IV or Basel 3.1) is due to be implemented by 2023, making banks more resilient during times of stress by increasing their capital buffers and reducing their reliance on short-term wholesale funding. Derivatives reforms have made the majority of interest rate and credit OTC derivatives trades to be centrally cleared through CCPs, improving transparency and reducing exposures, while collateral exchange in non-centrally cleared trades has been mandatory since 2016 for the largest market participants, reducing counterparty risk. MMFs investing in corporate debt are subject to more stringent liquidity requirements and mark-to-market their share prices to reduce the incentive for investors to run on the fund.

The market reforms have helped transform the fragile shadow banking sector into resilient market-based finance (MBF). The MBF sector, comprising mostly pension funds, insurance companies and other investment funds such as exchange-traded funds (ETFs), accounted for 49.5% of the global financial system in 2019, up from 42% in 2008, and plays an increasingly important role in providing financing to the real economy according to the Financial Stability Board (FSB) (FSB, 2020a). This has been broadly seen as a positive outcome for the resilience of the financial system as it diversifies risk away from banks and provides an alternative source of funding if banks are unable to perform their core lending activities according to the Financial Conduct Authority (FCA) (FCA, 2016). Importantly, market-based finance has replaced many shadow banking activities and is a more resilient source of financing. This is because it increases transparency by reducing the chain of intermediaries and system-wide leverage, does not rely on implicit sponsor support during times of stress, and has a more robust funding structure via long-term debt and equity rather than exclusively short-term wholesale financing (Adrian, 2017). Overall, the short-term wholesale-funded credit extension through various leveraged entities of shadow banking has been replaced by the simpler and more transparent capital allocation in financial markets through investment funds of market-based finance.

Nonetheless, the events of the market turmoil in March 2020 due to Covid-19 have shed light on the vulnerabilities prevalent in the MBF sector and its reliance on market liquidity. As economies were being shut down to stem the spread of the virus, financial markets experienced increased volatility due to the economic uncertainty, which led to large margin calls that forced leveraged institutions such as hedge funds to unwind their derivatives positions to raise cash to pay their obligations.[1] MMFs investing in corporate debt suffered large outflows once again as investors preferred to hoard cash and faced fire sales losses as the market liquidity of commercial paper evaporated, and other investment funds also faced large redemptions due to a flight-to-quality (FSB, 2020b). This dash-for-cash had a severe effect on government bonds, which are traditionally considered safe assets, as most participants preferred to sell what they perceived to be their most

[1] There was significant heterogeneity in initial margin increases across different CCPs which mainly depended on the asset classes they cleared as well as their margin methodologies. For example, while LCH Limited reported a relatively modest increase of 17% or $29.7 billion in total initial margin held for interest rates derivatives, CME Group reported an increase of 75% or $81.6 billion for its futures and options including equities derivatives in the first quarter of 2020 compared to the previous one according to the Futures Industry Association (FIA) (FIA, 2020). In addition, variation margin calls were even larger in the bilateral segment of the OTC derivatives market compared to the centrally cleared one according to the Bank of England (BoE) (BoE, 2020b).

liquid securities to raise cash. As a result, the dealer banks' capacity to absorb these sales was quickly overwhelmed, and government bond yields spiked. Only the highest-rated corporates were able to maintain access to market-based financing while most lower-rated ones resorted to drawing their credit lines from banks (Acharya and Steffen, 2020), which highlighted the fragility of the MBF sector as a source of funding in times of stress.

In order to restore stability to the financial system and ease the stress in government bond markets to facilitate the transmission of monetary policy, central banks introduced a wide range of measures. These included asset purchases, liquidity facilities and a temporary relaxation of certain regulatory measures such as the leverage ratio that were considered to be constraining dealers from intermediating in the financial markets. While this was effective in easing the strains in the financial system, this episode has highlighted the importance of examining the new vulnerabilities that have arisen after the financial crisis in order to effectively mitigate them.

1.2 Objectives and contributions

This thesis aims to provide insights into the role of different financial institutions in amplifying or mitigating systemic risk, and evaluate the impact of post-crisis regulations designed to curb this form of risk. A summary of each essay in this thesis is provided in this section, outlining their main results and contribution to the existing literature as well as to the current policy debate.

1.2.1 OTC derivatives markets clearing

The first essay examines the effects of the mandatory collateralisation of OTC derivatives contracts on counterparty, liquidity and systemic risks of the largest dealer banks and CCPs. This market reform, called non-central clearing, was introduced in 2016 in order to further reduce counterparty and systemic risks in the derivatives transactions that are not centrally cleared through CCPs according to the Basel Committee on Banking Supervision (BCBS) and the International Organization of Securities Commissions (IOSCO)

(BCBS-IOSCO, 2015). However, the clearing process that involves rigid margining and marking-to-market has been criticised for being procyclical, creating sharp increases in liquidity demand during periods of shortage in liquidity supply (Pirrong, 2014), which can have systemic implications as became evident during the dash-for-cash episode in March 2020 which was partly driven by margin calls (FSB, 2020b). Since non-central clearing greatly increases the demand for liquidity (Duffie et al., 2015), it is thus imperative to assess the effects of this regulation on the different forms of risk faced by the market participants. In this way we contribute to the academic literature that has mainly focused on the effects of central clearing on the different forms of risk (Duffie and Zhu (2011), Loon and Zhong (2014), Duffie et al. (2015)).

In order to answer our question, we develop a stress test network model of the largest bank dealers in the OTC derivatives markets and a representative CCP that clears a fraction of the total market activity, while the rest is bilaterally traded between the banks. The model thus incorporates both central and non-central clearing of OTC derivatives to examine the interplay between the two. This is important because the increased liquidity risk associated with the collateralisation of bilateral exposures increases the probability of bank defaults during market stress periods, and may result in higher losses for the CCP and the surviving banks as the CCP's loss mutualisation mechanisms are triggered (Pirrong (2014), Domanski et al. (2015), King et al. (2020)). Considering the repercussions of non-central clearing and the CCP loss mutualisation processes in isolation thus underestimates the risks imposed to the financial system. To this end, we model the operations of the CCP according to the current regulations (in terms of collateral collection and how they mutualise losses in case of a bank's default). This is a novel contribution to the literature, because we take into account all the different channels through which CCPs can transmit stress to their members and expand previous models of CCP contagion (Heath et al., 2016). Our framework thus captures the CCP-bank nexus that has come to the forefront of regulatory attention in the recent Covid-19 crisis, and our work aims to highlight the systemic implications of the CCP's mechanisms during a crisis (Huang and Takáts, 2020).

We calibrate the model to the banks' balance sheet data and we find that non-central clearing reduces counterparty and systemic risks, at the expense of higher liquidity risk.

Hence, the introduction of non-central clearing creates a significant risk-shifting effect via the transformation of counterparty to liquidity risk as derivatives exposures are mitigated via the exchange of liquid assets. In addition, we find that the CCP can face higher losses under non-central clearing, which increases its propensity to become a source of contagion for its members when its pre-funded resources are depleted. This is because non-central clearing increases the probability that the market participants will default on their obligations due to liquidity risk, hence increasing the losses for the CCP.[2]

Overall, our findings indicate that the post-crisis reforms in the OTC derivatives markets have been successful in reducing counterparty and systemic risks. However, it is important to understand that this comes at the expense of higher liquidity risk, which participants may not always be able to protect against as evidenced in the recent market turbulence. This is a topic that is high in the current regulatory agenda on the lessons learned from the March 2020 market turmoil (FSB, 2020b), and our results contribute to this debate.

1.2.2 ETFs and capital markets

The second essay examines the effects that ETFs have on the underlying assets' liquidity, prices and volatility. ETFs have experienced tremendous growth following the financial crisis, with global assets under management rising almost tenfold from $774 billion in 2008 to over $7 trillion in 2020 (ETFGI, 2020). Their popularity is attributed to the fact that they offer investors an inexpensive way to gain exposure to a wide variety of asset classes, combined with intraday liquidity by allowing their shares to be continuously traded on exchanges.

The growth of ETFs has sparked a debate across industry practitioners, academics, and policy makers on whether ETFs contribute to smooth market functioning, especially during times of stress. The academic literature has found that ETFs increase comovements of prices and liquidity of the underlying equities (Da and Shive (2015), Agarwal et al. (2017)) and

[2]We focus on the case of a systemic crisis where banks have to rely on their own funds to cover losses. In such cases, illiquidity can lead to insolvency if banks have to sell assets at fire sales prices, depressing their capital (Cont and Schaanning, 2016).

increase their volatility (Ben-David et al., 2018), but the effects on corporate debt securities are weaker due to the illiquid nature of the securities (Pan and Zeng (2017), Bhattacharya and O'Hara (2018), Agapova and Volkov (2018)). In addition, in the recent market turmoil of March 2020, ETFs appear to have acted as price discovery mechanisms, especially for illiquid underlying securities such as corporate bonds, as investors traded the more liquid ETF shares instead (BoE (2020b), Aramonte and Avalos (2020)). Yet, in previous instances such as the flash crash of 2010, it has been argued that ETFs propagated liquidity shocks to the underlying equities according to the report by the Commodity Futures Trading Commission (CFTC) and the Securities and Exchange Commission (SEC) (CFTC-SEC, 2010). Hence, the debate has not been resolved and understanding the mechanism through which ETFs affect the underlying securities is crucial as they increasingly dominate the markets in which they invest.

To shed light on this mechanism, we use a unique proprietary dataset of the Central Bank of Ireland containing all Irish ETFs and their holdings to look at the effects of Irish ETFs on the liquidity, prices and volatility of their underlying equities and corporate debt securities. Ireland is the main hub of ETFs in the euro area, with Irish ETFs managing €424 billion in assets as of September 2018, around two-thirds of the euro area total.

The rich dataset allows us to run panel regressions at the underlying security level on a daily frequency in order to assess the effects of ETFs while controlling for a host of other factors and including security and time fixed effects. We run the regressions for each underlying asset class separately, to understand the differential impacts of ETFs on them.

Our main findings can be summarised as follows. First, ETFs propagate liquidity shocks to the underlying equities but not to the underlying corporate debt securities, meaning that when ETFs become illiquid, they can also negatively affect the liquidity of equities but have no effect on the liquidity of corporate debt securities. Second, when demand shocks hit the ETF share prices, they can also strongly affect the prices of equities but only have a weak effect on the prices of corporate debt securities. Third, higher ETF ownership of equities increases their volatility, but higher ETF ownership of corporate debt securities decreases their volatility.

To understand why such differential effects occur across the two underlying asset classes, we rely on the theoretical framework that looks at links between assets that are formed via information channels. Information links are formed when investors use information from one asset to price the other (Cespa and Foucault, 2014), and we argue that ETFs form such information links with the underlying securities. However, the strength of the information link depends on the accessibility of the underlying assets. If the underlying securities are easy-to-trade with small transaction costs, such as exchange-traded equities, this facilitates the incorporation of information from the linked asset, and incentivises market participants to actively trade the underlying assets in order to exploit arbitrage opportunities with ETF shares which increases the transmission of shocks between markets. However, if the underlying securities are hard-to-trade with significant search and transaction costs, such as over-the-counter-traded corporate debt securities, this limits the ability of arbitrageurs to exploit arbitrage opportunities and results in a weak information link with the ETFs, limiting the transmission of shocks.

The proposed mechanism of information links and our empirical findings are consistent with how ETFs have behaved in previous periods of stress as well as previous findings in the academic literature (Ben-David et al. (2018), Agapova and Volkov (2018)), and by looking at both underlying asset classes together we are able to propose an explanation for these differential effects. According to CFTC-SEC (2010), when SPY, the largest US ETF tracking the S&P 500 index, became illiquid and suffered price declines in the flash crash of 2010, the market makers in the underlying equities increased their quoted bid-ask spreads or stopped intermediating entirely as they became uncertain about the value of the securities, at least as reflected in the ETF share price. In other words, the strong information link broke down during stress, which propagated the liquidity shock from the ETF to the underlying equities. More recently, in March 2020, many corporate bond ETFs were trading at large discounts to their underlying securities as the latter became completely illiquid and their prices remained stale while investors traded ETF shares instead. The demand shocks hitting the ETF share prices were not being transmitted to the underlying corporate debt securities because of their inaccessibility, which is a manifestation of the weak information link that exists between the two markets as the information present in the ETF shares was not being incorporated into the underlying securities.

The essay contributes to the debate on whether ETFs facilitate smooth market functioning by arguing that it depends on the accessibility of the underlying markets, which determines the strength of the information link that is formed between the two. This is important from a policy perspective as it sheds light on the mechanism through which ETFs can propagate shocks to the underlying securities through various channels, including their liquidity, prices and volatility. As ETFs continue to grow, their systemic importance will increase, so it is crucial to obtain a holistic view of how they can propagate shocks, and our paper contributes to this goal.

1.2.3 MMFs and money markets

The third essay examines the resilience of banks to liquidity shocks originating from MMFs. Following the events of the financial crisis, where MMFs investing in corporate debt experienced large runs which had a negative impact on the funding of the banks and as an extension on the provision of credit to the real economy (Ivashina and Scharfstein (2010), Acharya and Mora (2015)), the post-crisis regulatory framework of Basel III mandated that banks need to hold enough high-quality liquid assets (HQLA) to withstand a funding shock for a stress period of 30 days through their liquidity coverage ratio (LCR). However, LCR is inherently microprudential in nature as it does not take into account the interconnectedness that exists between financial sectors (Bonner et al., 2018). As such, the question of whether it helps in mitigating systemic liquidity risk, a macroprudential concern, remains open and is the focus of this essay.

This essay focuses on a specific aspect of systemic liquidity risk, the direct interconnectedness that exists between banks and MMFs, which facilitate the short-term liquidity needs of financial institutions by investing in commercial paper, certificates of deposit and repurchase agreements (repos). While regulations were introduced to reduce MMFs' fragility following the financial crisis, they again experienced runs during the recent Covid-19 crisis due to investors' flight-to-quality and search for cash. Without regulatory intervention, the run could have triggered widespread contagion, propagating systemic liquidity risk (Cunliffe (2020), BoE (2020a)). The fragility of MMFs during the financial crisis has been well-documented in the academic literature (Kacperczyk and Schnabl (2013), Chernenko and Sunderam (2014), Strahan and Tanyeri (2015), Schmidt et al. (2016)), but there is scant empirical work looking at the post-crisis period following the introduction of MMF regulations and this essay fills this gap.

To answer my research question, I develop a network model of MMFs and banks and assess whether redemptions incurred by the former can significantly impair the available liquidity of the latter. The redemptions can be modelled either exogenously (liquidity risk) or endogenously as a result of losses due to a bank default (i.e. a Lehman scenario - counterparty risk). To satisfy the redemptions, the MMFs stop reinvesting the proceeds from maturing securities which creates a funding shortfall for the banks. The banks then attempt to cover this shortfall in the overnight interbank market, which can create upward pressure on interbank rates, propagating liquidity stress. In extreme cases where MMFs have insufficient cash to satisfy redemptions, they resort to asset sales. Due to the absence of an active secondary market of money market securities, they ask the issuing banks to buy back the assets, and the latter can impose haircuts if they have insufficient liquidity or are unwilling to provide it, creating fire sales losses for MMFs and a new round of redemptions. Importantly, the model incorporates the post-crisis US MMF regulations designed to strengthen their resilience and mitigate first-mover advantages to accurately capture the dynamics that can unfold during stress.

The model is calibrated to the security-level US prime MMF holdings data as of December 2017 which provide a detailed picture of the network of exposures between MMFs and the largest issuer banks of money market securities. My main finding is that LCR is effective at protecting the banking sector against systemic liquidity risk arising from the interconnectedness with the MMF sector, as the banks are able to retain their regulatory LCR requirement of 100% even in the presence of very large MMF redemption shocks not observed historically. The liquidity buffers held by both banks and MMFs have increased their resilience, although when banks are unwilling to accommodate asset sales the resulting fire sales can create significant losses for the MMFs. This is consistent with what was observed in the recent market turmoil, and my results highlight the fragility of MMFs during times of stress due to the illiquidity of their holdings which necessitates the review of the relevant regulatory framework, an important topic in the current regulatory agenda (FSB, 2020b).

1.3 Conclusion and policy implications

To summarise, the findings of this thesis provide several policy implications. On OTC derivatives markets, we find that CCPs reduce systemic risk as predicted by regulators, but they can also increase stress in the financial system if their own resources are depleted or if they increase margins procyclically. Hence, the regulatory stress testing methodologies (e.g. the European Securities and Markets Authority (ESMA) EU-wide CCP stress test) should also incorporate CCPs' actions during stress and how they affect their members to gain a more holistic understanding of the dynamics that can crystallise. This would allow them to capture feedback effects between banks and CCPs (e.g. through the activation of the CCPs' loss mutualisation mechanisms), as well as the broader impact of these effects on banks' credit provision to the real economy (Huang and Takáts, 2020). Furthermore, we find that derivatives clearing reduces counterparty risk at the expense of higher liquidity risk, which can have systemic implications if market participants engage in fire sales to generate cash to pay their margin obligations (as hedge funds did in March 2020 (FSB, 2020b)), or if they hoard liquidity as a precautionary measure (as banks did (Huang and Takáts, 2020)). To the extent that banks prefer to hold liquid assets, this can also have a detrimental effect on loan origination, which can negatively affect the real economy (Cornett et al., 2011). Hence, it is important that the regulatory authorities examine the margining practices in centrally and non-centrally cleared markets to ensure that they do not amplify funding strains during times of stress and disrupt the provision of credit to the real economy as a result.

On ETFs, we find that they have a differential impact on the liquidity, prices and volatility of equities and corporate debt securities, and we posit that this occurs because of their different levels of accessibility. Hence, in order to understand whether ETFs can propagate shocks to the underlying securities, policymakers should monitor markets with which ETFs form strong information links that can break down during stress, as happened with the equity market in the flash crash of 2010. In this way, potential stress mitigation mechanisms that could be adopted include security-level circuit breakers that would pause trading in these securities if their prices moved sharply due to a liquidity crash (CFTC-SEC, 2010).

On MMFs and systemic liquidity risk, my findings suggest that the post-crisis reforms have made the banks more capable to withstand liquidity shocks, but the MMFs are still susceptible to fire sales losses if the market liquidity of commercial paper evaporates, even after taking into account their higher liquidity buffers as a result of the reforms. Hence, policymakers should consider whether the market structure of commercial paper needs to be reformed to encourage an active secondary market and increase its liquidity, as is currently the case with other money market securities such as certificates of deposit. Indeed, my findings showcase that while MMFs' losses are not significantly negatively correlated with their liquidity holdings, they are very highly positively correlated with banks' reluctance to buy back assets as measured by the haircuts they impose on such sales. As a result, from a policy perspective it would be more beneficial to ensure the continuous existence of market liquidity rather than increase MMFs' liquidity buffers further in order to improve their resilience.

Chapter 2

Systemic Stress Testing under Central and Non-Central Clearing[1]

Abstract

The revised OTC derivatives regulatory framework mandated the collateralisation of non-centrally cleared contracts. We develop a stress-testing network model of the largest market participants to assess the effects of this reform on bank-level and systemic risks. We compare defaults due to counterparty and liquidity risks and systemic losses in the regime with and without non-central clearing. We find risk-shifting effects from counterparty to liquidity risk and reduction of systemic risk at the expense of increased contagion from central counterparties. The expansion of central clearing is found to reduce systemic risk, supporting regulatory initiatives.

[1]This essay is based on the working paper titled "Systemic Stress Testing under Central and Non-Central Clearing" co-authored with Barbara Casu (The Business School (formerly Cass)) and Elena Kalotychou (Cyprus University of Technology).

2.1 Introduction

The lack of market transparency associated with over-the-counter (OTC) derivatives contracts and the widespread losses during the financial crisis prompted the response of the regulators who initiated a reform programme aimed at containing counterparty and systemic risks in the financial system. The G20 leaders mandated the clearing of all standardised OTC derivatives contracts through central counterparties by the end of 2012 and the introduction of higher capital requirements for bilateral contracts cleared between counterparties (G20, 2009).[2] The clearing mandates were later strengthened by collateral requirements for bilateral trades (G20, 2011). Non-central clearing, formally introduced in 2016, imposed the mandatory collateralisation of bilaterally traded OTC derivatives through the exchange of margins between counterparties.[3]

The OTC derivatives market reforms have two main goals. First, promoting central clearing by creating cost incentives (lower capital and collateral requirements compared to bilateral clearing) with a view to reduce systemic risk by allowing for greater netting of exposures through CCPs. Second, curbing counterparty risk through the establishment of a rigorous and transparent margining mechanism extended to embrace bilateral trades.

As the reforms have reshaped the OTC derivatives markets, understanding their implications is crucial for numerous reasons. First, as a result of the new clearing mandate CCPs have become the dominant counterparties in several derivatives markets.[4] Second, rather than reducing risk the new clearing regulations may result in redistributing risk away from derivatives positions to other creditors of distressed firms, potentially of

[2]Central clearing involves trading contracts through a clearing house, aka central counterparty (CCP), which interposes itself between counterparties by becoming the buyer to every seller and the seller to every buyer. As the bilateral trade ceases to exist the CCP concentrates counterparty risk in exchange for collateral in the form of initial margin (IM) and contributions to a default fund (DF) which is used to mutualise losses across clearing members (CMs). CCP protection is further established by daily marking-to-market all positions and transferring cash-flows from losing counterparties to winning ones upon adverse price movements through the collection of variation margin (VM).

[3]The G20 mandate was enforced via the Dodd-Frank Act in the US and the European Market Infrastructure Regulation (EMIR) in the EU.

[4]The fraction of centrally cleared credit default swap (CDS) contracts increased from 10% to 55% in terms of gross notional from 2010 to 2018 according to Bank for International Settlements (BIS) data. Central clearing is predominant in the OTC interest rate derivatives market with CCPs managing 75% of total positions globally as of December 2018 (BIS, 2019) and is gaining ground in other derivative asset classes (BIS, 2017).

systemic importance. The redistribution of risk could turn out to be destabilising for the financial system. Third, the clearing process that involves rigid margining and marking-to-market has been criticised for being procyclical, creating sharp increases in liquidity demand during periods of shortage in liquidity supply, thereby exacerbating systemic risk (Pirrong, 2014). This was evidenced in March 2020 when market turbulence led to a dash-for-cash following margin calls, negatively affecting traditionally safe markets such as US government bonds and aggravating redemptions from money market funds (BoE (2020b), FSB (2020b)).

In this paper, we assess the impact of the introduction of the mandatory collateralisation of bilaterally traded derivatives, which we refer to as non-central clearing. While non-central clearing of OTC derivatives is expected to reduce counterparty risk and spillover effects, it may do so at the expense of the liquidity of market participants (BCBS-IOSCO, 2015). Motivated by the documented concerns that liquidity risk may be a much more significant source of stress than counterparty risk in cleared OTC derivatives markets (Cont, 2017), our work focuses on disentangling and quantifying the effects of non-central clearing on these two forms of risk for both the largest dealer banks as well as the CCP. Acknowledging new forms of stress that can crystallise in the new regulatory environment is key for preempting potential adverse effects of the new mandate.

The concept of risk transformation, first coined by Cont (2017), posits that clearing does not eliminate counterparty risk but transforms it into liquidity risk as exposures are mitigated via the exchange of margins (IM and VM) in the form of liquid assets. Hence, the introduction of non-central clearing may create a risk-shifting effect, reducing potential losses from exposures and the risk of insolvency, but increasing disproportionately the liquidity encumberment of market participants, rendering them more vulnerable to liquidity shocks that can occur in times of market stress. We test the risk transformation hypothesis by using the introduction of non-central clearing as the vehicle for providing counterparty risk protection through the mandatory bilateral exchange of liquid assets.

In addition, improved understanding of the channels through which losses arise in cleared OTC derivatives markets, particularly in the aftermath of a major regulatory intervention, allows for a more accurate appraisal of the risks involved and the role of the CCP as a potential source of contagion for its members. The increased liquidity risk associated with the collateralisation of bilateral exposures increases the probability of CM defaults during market stress periods and may result in higher losses for the CCP and the surviving CMs as the CCP's loss mutualisation mechanisms are triggered (Pirrong (2014), Domanski et al. (2015), King et al. (2020)). Thus, considering the repercussions of non-central clearing and the CCP loss mutualisation processes in isolation underestimates the risks imposed to the financial system. Our framework captures the CCP-bank nexus that has come to the forefront of regulatory attention in the recent Covid-19 crisis, and our work aims to highlight the systemic implications of the CCP's mechanisms during a crisis (Huang and Takáts, 2020).

We extend the literature which has mainly focused on central clearing, by evaluating the effects of non-central clearing of OTC derivatives on counterparty, liquidity and systemic risks and their interaction. Our contribution is twofold. First, on the methodological front we contribute to existing empirical work on CCP modelling and, in particular, the modelling of the loss allocation mechanisms of the clearing house. Building on the methodology of Heath et al. (2016) we construct a network model of the largest dealer banks in the OTC derivatives markets and a fictitious CCP taking into account the various mechanisms through which the CCP allocates uncollateralised losses to the CMs. The model dynamics unfold in two rounds. In the first round, an exogenous market shock creates VM exchanges in the system and potential defaults due to a) liquidity risk arising from insufficient liquid resources to meet VM obligations, and b) counterparty risk attributed to large equity losses following missed VM gains from defaulted counterparties. The second round captures the way the CCP mutualises the losses due to missed VM gains across the surviving participants through further default fund contributions (over and above those originally collected) and haircuts on their VM gains. This process can pose both liquidity and counterparty risks to CMs. To our knowledge, this paper is the first to comprehensively model the CCP's loss mutualisation mechanisms to reflect the new regulatory framework. Therefore, it provides the necessary framework to assess whether the feedback effect between the banks and the CCP is amplified with the introduction of non-central clearing during times of stress.

Second, we contribute to three strands of empirical literature on derivatives clearing. On counterparty risk, Duffie and Zhu (2011) argue through a theoretical model that central clearing may not always reduce counterparty risk as fragmenting central clearing services by assigning separate CCPs to each derivative asset class increases exposures. However, Loon and Zhong (2014) find empirically that the introduction of central clearing in the CDS market reduced counterparty risk. Our analysis complements the prior work by assessing whether non-central clearing further reduces counterparty risk in the OTC derivatives markets. On liquidity risk, Duffie et al. (2015) show that the introduction of non-central clearing greatly increases the demand for collateral due to the limited netting benefits of bilateral trading, while the expansion of central clearing reduces it due to multilateral netting. We add to this line of research by analysing the implications of the increased collateral demand due to the introduction of non-central clearing for financial stability. On systemic risk, Heath et al. (2016) examine the effect of increased central clearing on the topology and stability of the financial network and find that CCPs act as a source of stability in the system even in the presence of large market shocks. Paddrik et al. (2020) develop a network model of the cleared CDS market and calibrate it to trade repository data to assess contagion effects under a stress scenario. They document significant losses and defaults of market participants, even though the CCP avoids default by using its pre-funded resources. On this front, our paper provides evidence in regards with the CCP's propensity for contagion following the introduction of non-central clearing. We pursue this by considering a range of stress scenarios which could potentially exhaust the CCP's pre-funded resources, and quantifying the amount of stress imposed on its members.[5]

In order to test our hypothesis on the effectiveness of non-central clearing, we calibrate our model using annual report data on the positions of the largest participating banks in

[5] The theoretical branch of the literature concerns the optimal central counterparty design. Biais et al. (2012) examine the implications of full vs. partial protection offered by CCPs in the presence of aggregate risk. Acharya and Bisin (2014) consider the counterparty risk externality generated by the opaqueness of the OTC markets and the CCP's ability to eliminate it. Glasserman et al. (2016) argue for the need for CMs to disclose information about their positions across multiple CCPs in order for the latter to impose accurate margins. Amini et al. (2015) propose a CCP design based on fees and default fund policies that reduces systemic risk and improves aggregate surplus. Menkveld (2016) shows that a certain degree of crowding in trades is socially optimal because it increases overall investment.

the global OTC derivatives markets and compare the systemic losses before and after the introduction of non-central clearing. We measure systemic risk as the total equity losses that occur in the system due to OTC derivatives trading during stress conditions.[6] Importantly, these losses pertain both to market-induced shocks (first-round) and feedback effects (second-round). Our model belongs to the class of macroprudential stress testing models which have been developed following the financial crisis to capture the interdependencies between financial institutions that facilitated the propagation of shocks during the crisis.

Our main finding is that the introduction of non-central clearing substantially reduces counterparty and systemic risks under all market conditions. However, the reduction of counterparty and systemic risks comes at the expense of higher liquidity risk which becomes substantial during extreme market stress due to large VM obligations. Non-central clearing severely impairs the CMs' ability to pay those obligations in periods of stress due to higher liquidity encumberment, which triggers a significantly higher number of liquidity-driven defaults, although the protection offered by non-central clearing reduces the resulting losses in bilateral trading. As a result of the higher number of defaults, the CCP suffers bigger losses and in turn becomes a significant source of contagion in extremely adverse market conditions, distributing higher losses to the surviving members in the second round. Nonetheless, we find that the reduction of (first-round) losses due to the collateral in bilateral trades in the regime with non-central clearing more than offsets the increase of (second-round) losses due to the greater fragility of the CCP , which results in a reduction of overall systemic losses.

Second, our results provide empirical support for the risk transformation argument. We show through simulations that in extreme market conditions the number of liquidity-triggered defaults increases by 60 percent whereas the counterparty-triggered defaults decrease by 50 percent. Hence, the introduction of non-central clearing creates a significant risk-shifting effect via the transformation of counterparty to liquidity risk. In addition, we

[6] In our context, systemic risk propagates among banks through bilateral transactions similarly to Rochet and Tirole (1996) although there exist several other channels of contagion including fire sales (Acharya and Yorulmazer (2008), Cont and Schaanning (2016)), liquidity spirals (Brunnermeier and Pedersen, 2009), herding behaviour (Acharya (2009), Farhi and Tirole (2012)) and runs (Pedersen (2009), Diamond and Dybvig (1983)). Models introduced to measure individual contributions to systemic risk in terms of market equity losses include Systemic Expected Shortfall (Acharya et al., 2017) and CoVaR (Adrian and Brunnermeier, 2016).

find that liquidity risk is a much more severe source of stress than counterparty risk in cleared markets as it accounts for the vast majority of defaults.

Third, we test the expectation of regulatory authorities that the requirement of non-central clearing may promote financial stability by incentivising market participants to switch to central clearing due to lower collateral costs (BCBS-IOSCO, 2015). By simulating various proportions of central clearing in the market, we find evidence in favour of the expansion of central clearing because increased multilateral netting reduces exposures and first-round losses following market shocks. The large reduction of first-round losses reduces overall systemic risk even though the second-round losses increase as the CCP becomes more dominant and its propensity for contagion increases. Furthermore, since the expansion of central clearing reduces bilateral trading, the effects of non-central clearing are found to be insignificant when the CCP is the counterparty to most transactions. This showcases that non-central clearing can indeed provide incentives to market participants to migrate to central clearing in order to mitigate the effects of higher collateral costs in bilateral trading.

Against the backdrop of major regulatory overhauls whose impact is expected to be economically significant given the size of the OTC derivatives markets, our results have important policy implications. First, the introduction of non-central clearing appears beneficial for financial stability but at the cost of higher liquidity risk and related defaults during extreme market stress, which has adverse consequences for the stability of the CCP and the surviving market participants. In the presence of large shocks, the liquidity crunch can have systemically destabilising effects if market participants engage in fire sales (as hedge funds did in March 2020 (FSB, 2020b)), or if they hoard liquidity as a precautionary measure (as banks did (Huang and Takáts, 2020)). Hence, the regulatory authorities should examine the margining practices in centrally and non-centrally cleared markets to ensure that they do not amplify funding strains during times of stress. Second, to the extent that non-central clearing prompts counterparties to migrate their bilateral positions to centrally cleared ones, the resulting expansion of the CCP can reduce systemic risk. However, our findings suggest that CCPs can also increase stress in the financial system if their own resources are depleted or if they increase margins procyclically. Hence, the regulatory stress testing methodologies should also incorporate CCPs' actions during stress and how they affect their members to gain a more holistic understanding of the dynamics that can crystallise (Domanski et al. (2015), Huang and Takáts (2020)).

The rest of the paper is organised as follows. Section 2.2 provides an overview of the key regulations regarding the clearing of OTC derivatives, section 2.3 describes the model, section 2.4 presents the data used in our study and section 2.5 presents the empirical results. Section 2.6 discusses the results of sensitivity analysis and finally section 2.7 concludes.

2.2 Clearing regulations

In this section we briefly overview the clearing regulations in centrally and non-centrally cleared transactions that we use in our model to derive our results. The IM collected as collateral at contract initiation is intended to cover at least 99% of exposures movements under normal market conditions over the margin period of risk - the time required for positions to be closed out following a default - as stated in the principles developed by the Committee on Payment and Settlement Systems (CPSS) and the International Organization of Securities Commissions (IOSCO) (CPSS-IOSCO, 2012). Regulators have set the holding period at five days for centrally cleared positions and ten days for bilateral transactions that are non-centrally cleared via the mandatory exchange of IM between counterparties (BCBS-IOSCO, 2015).

Since the positions are marked-to-market daily, the maximum exposure the participants have at any point in time is the daily price variation and is managed by the VM exchange between counterparties. VM represents the change in value since the last marking-to-market so that at the end of each day the value of the cleared contract is zero if the VM is transferred successfully (no exposure). This prohibits large exposures from accumulating during the life of the contract, thus reducing counterparty risk. In non-centrally cleared trades, the exchange of VM was made mandatory for all market participants in March 2017, although it also existed in various forms before the crisis (Gregory (2014), International Swaps and Derivatives Association (ISDA) ISDA (2014b)). It is important to note that in centrally cleared trades VM must typically be paid in cash while IM can be in the form of high-quality liquid assets (HQLA). In non-centrally cleared trades, both IM and VM can be settled using HQLA (BCBS-IOSCO, 2015).

Regarding centrally cleared trades, in accordance with international standards (CPSS-IOSCO, 2012), the CCP requires CMs to contribute to the default fund as an additional line of defence on a pro-rata IM basis. The DF is used to mutualise uncollateralised losses (i.e. in excess of IM) in the case of a CM default among the surviving members. The DF of systemically important CCPs is calibrated to Cover-2, i.e. expected to cover the uncollateralised losses arising from the simultaneous default of the two largest CMs in terms of exposures under extreme but plausible market conditions. These conditions are typically modelled using stress tests that assess the CMs' gains and losses during historical or simulated stress conditions. Even though these stress tests are designed to capture the effects of market turbulence on the centrally cleared portfolios, if they were to materialise they would also affect the CMs' bilateral positions which could amplify their losses and make them more likely to default. Furthermore, the CCP also commits part of its capital to absorb losses. This "skin-in-the-game" is typically used after the defaulting CM's IM and DF contributions and before other CMs' DF contributions in order to incentivise the CCP to maintain sound risk management practices. However, this capital is typically small so as not to endanger the solvency of the CCP and compromise its main objective of protecting surviving CMs.

Upon depletion of the pre-funded resources additional losses are managed through the CCP recovery mechanism contained in the default management process (DMP) which includes the Powers of Assessment and variation margin gains haircuts (VMGH) to the winning counterparties. Under the Powers of Assessment, the CCP may request from surviving CMs to provide additional resources limited to a certain multiple of their original DF contributions in order to repay its obligations. This transforms the CCP into a possible source of contagion by demanding liquidity in times of extreme market stress when multiple CMs are likely to be constrained (Pirrong, 2014). If the Powers of Assessment prove inadequate to cover the losses borne by the CCP, the residual losses are allocated on a pro-rata basis to the winning counterparties by applying a VMGH. This has been proposed as an effective loss allocation mechanism at the end of the risk waterfall by simulating the effects of general insolvency.

While under normal conditions the CCP is market-neutral since for every buyer there is a seller, when a default occurs it becomes the owner of the centrally cleared portfolio of the defaulted CM. This exposes the CCP to market risk which would make it liable to unlimited future VM payments to winning counterparties and hence require unlimited resources. As a result, the successful utilisation of its resources and the recovery tools is conditional on returning to a matched book. This is achieved via an auction of the defaulting portfolio where the surviving CMs act as bidders (ISDA, 2015). While the CMs have the right to bid negatively, i.e. request compensation from the CCP in order to claim ownership of the defaulting portfolio, the CCP incentivises sensible bidding behaviour by allocating uncollateralised losses according to the ranking of the bids. Hence, CMs who do not bid at all will be asked to replenish funds via the Powers of Assessment first in full and then sequentially for other CMs according to bid competitiveness. It follows that the winner of the auction will have its resources claimed last if necessary and hence the probability of it having to replenish the DF with additional resources will be minimal. For a more detailed description of the mechanisms of the DMP see ISDA (2015).

2.3 Model

Our modelling framework evolves over a period of three days, $t = \{0, 1, 2\}$, in order to capture the key dynamics of clearing following a stress event. The time frame is aligned with the clearing operations that occur at a daily frequency and the daily marking-to-market of positions. Table 2.1 summarises the model dynamics.

At time $t = 0$ we construct the bilateral OTC derivative exposures network based on the available aggregate data as well as a fictitious CCP that clears a fraction of total derivatives activity. While the CMs stand for real banks, the CCP is not real for a number of reasons.

First, analysing the rare and extreme event of a CCP failure is beyond the scope of this study.[7] Second, modeling of the breakdown of total exposures of CMs to real CCPs

[7] Historically there have been only four CCP defaults, the most severe one being related to the Hong Kong

Table 2.1: Model dynamics

Time	Round	Description
$t = 0$	Baseline	Initial configuration
$t = 1$	First day effects	Shock on derivative asset triggers VM; potential VM defaults due to liquidity risk cause defaults due to counterparty risk
$t = 2$	Second day effects	CCP triggers DMP if applicable; unfunded losses are allocated to CMs

is challenging due to data limitations as we do not observe the fraction of exposures centrally cleared by various real CCPs. Nonetheless, given our focus on CMs equity losses, a fictitious CCP that acts as a market representative does not pose any drawback to the analysis so long as its operation complies with the prevalent regulations.

We start the analysis by calculating the IM collected by the CCP and calibrating its DF to Cover-2. These calculations are simplified in the sense that we only consider the cost of protection against market risk while in reality CCPs also charge for other risks, e.g. highly concentrated positions in the market.[8] Following this calculation, we consider two different configurations, one in which the CMs also post IM between themselves in bilateral trades (non-central clearing) and one in which they don't. This allows us to assess the effects of non-central clearing on our model results. In both cases the CCP remains active and clears the same fraction of derivatives activity, collecting the same amount of collateral. We treat the asset class as a representative risky asset that the CMs trade with each other.

The clear-cut distinction between the two configurations enables the straightforward evaluation of the effects of collateralising bilateral trades. It is important to note that this distinction is stylised since some bilateral trades exchanged collateral even before the introduction of non-central clearing, although they tended to be undercollateralised

Futures Exchange in 1987 (Berndsen, 2020). For a description and empirical analysis of CCP failures see Bignon and Vuillemey (2018) and Cox (2015).

[8]The exact level of detail in calculating margins is not relevant in terms of assessing the incremental impact of non-central clearing provided it remains invariant in the two regimes. In subsection 2.6.1 we discuss the model results when the CCP collects double the resources it does in the baseline configuration in order to assess the effect on overall systemic risk. Our results on the effects of the introduction of non-central clearing are robust.

(Gregory, 2014). In addition, we do not endogenise the change of market activity in response to the implementation of non-central clearing in our model, i.e. we assume that the positions remain the same before and after introducing non-central clearing. Ghamami and Glasserman (2017) and Bellia et al. (2017) find several cases in which bilateral trading remains more capital and collateral efficient even after the introduction of non-central clearing than a full migration to central clearing, while Cenedese et al. (2020) discuss the incentive of market participants to make contracts non-standardised to circumvent the clearing mandates. As such, the extent of change in the market activity as a result of the new regulation remains ambiguous.[9] Nonetheless, comparing the two configurations in this way allows us to capture the transformation of counterparty to liquidity risk and its systemic implications through the introduction of non-central clearing in a simplified framework that incorporates the key drivers behind these risks.

At time $t = 1$ we commence the stress test by applying exogenous shocks of various magnitudes on the asset which create VM losses and gains in the system. We assume that VM is exchanged in bilateral transactions even without non-central clearing because as stated in section 2.2 the majority of contracts already had such arrangements in place before the introduction of the new regulations. In our context, the additional collateral demand is due to the exchange of IM in bilateral transactions which puts additional liquidity strain on the CMs.

We allow the CMs to react to the shock by attempting to close their positions and regain liquidity through the return of IM in order to fulfil their VM obligations. This behaviour follows from Brunnermeier and Pedersen (2009) who model budget-constrained dealers in a similar way. Hence, after the shock we perform an optimisation in which the CMs trade the asset with each other subject to their budget constraints. The larger the shock, the less likely it is that everyone will be able to achieve their goal, which leads to more defaults.

We assume that the CMs pay their IM and VM obligations using their HQLA (which include cash reserves) as discussed in the previous section and, in the baseline scenario, that they are under liquidity stress if their liquidity coverage ratio (LCR) drops to less than 100%. LCR is a regulatory ratio introduced in Basel III that requires banks to have enough

[9] In subsection 2.5.2 we consider the case where a higher fraction of trades are cleared through the CCP to assess the potential effects of a migration to central clearing.

HQLA to repay their obligations under a severe 30-day stress scenario where funding sources are withdrawn. This ratio under normal market conditions must be at least 100%, i.e. banks must have HQLA equal or greater than the projected obligations during the stress period, although during actual stress the banks are expected to use their HQLA reserves. The banks typically hold HQLA reserves in excess of their projected obligations and we assume that they have those excess reserves available for derivatives obligations, with the rest used for other operations. Hence, CMs whose VM obligations breach their LCR minimum requirements are assumed to default due to liquidity risk.[10] We treat the non-cash portion of HQLA as infinitely liquid and readily convertible to cash without the risk of fire sales, given that VM obligations for centrally cleared trades are settled in cash.[11]

CMs whose counterparties default on their VM obligations suffer equity losses through profit and loss. We assume that CMs default due to counterparty risk if their capital adequacy ratio (CAR) drops to less than 8% as a result of these losses. CAR is a regulatory ratio of minimum capital requirements that banks must always satisfy, introduced in Basel III.

At time $t = 2$ the CCP assigns uncollateralised losses it suffers, if any, to the surviving CMs. It first performs an auction of the defaulting portfolio in order to return to a matched book. It then uses the available IM and DF resources to cover losses. If these prefunded resources are insufficient, it calls on its Powers of Assessment by asking surviving CMs to replenish the DF according to their bidding behaviour, posing a liquidity risk to them. As such, our model quantifies the domino effects that may originate from the loss allocation mechanisms of the CCP that have been theoretically documented. Domanski et al. (2015) argue that the unexpected liquidity demands originating from the CCP's recovery mechanisms may stress the CMs and in extreme cases cause a default cascade. We estimate the potential number of defaults in such cases due to liquidity stress.

In the most extreme cases when the Powers of Assessment prove inadequate, the CCP proceeds to VMGH, which translates into additional equity losses for the CMs that expect

[10] We discuss the model results assuming a minimum LCR of 70% in subsection 2.6.2.

[11] In unreported results, we have run the model assuming that banks have a fraction of HQLA available to pay their derivatives obligations based on the reported ratio of projected derivatives outflows to total outflows. The pool of available HQLA is smaller compared to our baseline methodology leading to more banks being under liquidity stress, but the results are qualitatively similar.

VM receipts from the CCP, posing a counterparty risk to them. Since this occurs only in the most extreme market conditions when the CMs are stressed as well, our model captures the wrong-way risk that has been reported by Pirrong (2014). In such cases the activation of the CCP's recovery mechanisms is likely to put additional pressure on the system exactly when it is at its most vulnerable. We quantify the systemic losses that may crystallise under such conditions due to VMGH.

The completion of the DMP typically occurs within five working days (ISDA, 2015) but for simplicity we assume it takes place on a single day, $t = 2$. While this may overestimate the amount of stress the CCP can realistically impose on the CMs on a single day, by not considering multiple days we are also neglecting the potential amplification of losses if asset price movements create further VM obligations for the CCP.

Our aggregate measure of systemic risk is the total equity losses of CMs on days 1 and 2 which we use to assess the effectiveness of non-central clearing. We proceed with a detailed discussion of each step.

2.3.1 Initial Configuration ($t = 0$)

Consider a population of n banks belonging in the set of network nodes $N = \{1, 2, \ldots, n\}$. The presence or absence of a connection between any two banks through derivative exposures is determined by the adjacency matrix $\boldsymbol{I}$. This is a $n \times n$ matrix that takes values of 1 if there is an edge between banks i and j ($I_{ij} = 1$) and 0 otherwise. The main diagonal of the matrix is zero since the banks do not have exposures to themselves ($I_{ii} = 0 \; \forall \; i \in N$). The network is directed since a bank may have an exposure to a counterparty but the reverse need not be true.

We assume a core-periphery network structure which has been identified in OTC derivatives markets among others by Craig and Von Peter (2014) and Markose (2012). To configure the network, we use the connectivity priors assumed in a study by the Macroeconomic Assessment Group on Derivatives (MAGD) to construct the adjacency matrix (MAGD, 2013). Specifically, we assume that the core (large) banks trade with each other with 100% probability, they trade with the periphery (small) banks with 50% probability and the latter trade with each other with 25% probability and generate random numbers from the Bernoulli distribution in accordance with these priors.[12] In total, we generate 100 adjacency matrices and repeat the stress testing exercise for each random network, providing results as averages of the 100 simulations.

Next, we construct the $n \times n$ bilateral exposures matrix $\boldsymbol{X^0}$. We define the OTC derivatives obligation owed by bank i to bank j as X^0_{ij}. Thus, the sum of columns for row i represents the observable total gross liabilities (L^0_i) of bank i while the sum of rows for column i represents the observable total gross assets (A^0_i) as given by the balance sheet data. We infer the bilateral gross exposures X^0_{ij} by minimising the errors in the row and column sums, following Heath et al. (2016):

$$\min_{X^0_{ij}, X^0_{ji}} \sum_i \left[\left| A^0_i - \sum_j X^0_{ji} \right| + \left| L^0_i - \sum_j X^0_{ij} \right| \right] \tag{2.1}$$

subject to:

$$X^0_{ij} = 0 \text{ if } I_{ij} = 0$$

$$0 \leq X^0_{ij} \leq \min(A^0_j, L^0_i)$$

The goal of optimisation (2.1) is to estimate the bilateral exposures matrix by providing column and row sums as close as possible to the available bank data of liabilities and assets respectively. If the adjacency matrix has an element with a value of zero then the corresponding exposure is also zero and the upper bound is the minimum of the total assets for the specific column and the total liabilities for the specific row. By construction, the optimisation equates total assets and total liabilities, $\sum_i \sum_j X^0_{ji} = \sum_i \sum_j X^0_{ij}$, hence the solution of the objective function is equal to the difference between the total assets and total liabilities of the data. This implies that the system is assumed to form a complete economy.

Following Heath et al. (2016), the bilateral gross notional positions are estimated by multiplying the values in each row of the exposures matrix $\boldsymbol{X^0}$ by the ratio of gross notional liabilities to gross market value of liabilities. The gross notional positions matrix is denoted $\boldsymbol{G^0}$. Finally, the net notional positions matrix is simply calculated as $\boldsymbol{N^0} = \boldsymbol{G^0} - (\boldsymbol{G^0})^{\mathbf{T}}$, i.e.

[12]Our results are robust to denser and sparser network configurations.

the difference between the gross notional positions matrix and its transpose. The matrix $\boldsymbol{N^0}$ is skew symmetric such that $N^0_{ij} = -N^0_{ji}$.

We introduce the CCP by augmenting the matrix $\boldsymbol{N^0}$ with an additional row and column to create the new matrix $\boldsymbol{W^0}$. Let $s \in [0,1]$ denote the fraction of centrally cleared transactions. Then $W^0_{ij} = (1-s)N^0_{ij}\ \forall\ i,j \in N$ and $W^0_{ij} = \sum_{p=1}^{n} sN^0_{ip}\ \forall\ i \in N$ and $j = n+1$. In addition, $W^0_{ij} = -W^0_{ji}\ \forall\ j \in N$ and $i = n+1$. The matrix $\boldsymbol{W^0}$ remains skew symmetric.

We can now calculate the IM using the matrix $\boldsymbol{W^0}$. As stated in section 2.2, the minimum requirement for the calculation of the IM is to cover at least 99% of exposures movements, which is typically estimated with a value-at-risk (VaR) model. We adopt a Monte Carlo approach in order to be able to update the IM at $t = 2$. Specifically, we model the asset as a representative interest rate swap with price dynamics following an Ornstein-Uhlenbeck process:

$$dP_t = -kP_t dt + \sigma_t dZ_t \tag{2.2}$$

where k is the speed of mean reversion, σ_t is the time-varying volatility and Z_t is a one-dimensional Brownian Motion under the real-world probability measure. We assume that the long-run mean value of the contract is zero which implies a "fair" contract. The value of k is irrelevant so we set it arbitrarily at 1. However, the volatility parameter is crucial in setting the IM. We discuss the calibration of this parameter in section 2.4.

We simulate 1000 paths and calculate the margin as the maximum between the lower 1% and upper 99% percentiles of the price differences dP_t as done in practice by CCPs in order to protect themselves from both upswings and downswings. Denote this value as m_0:

$$m_0 = \max(|p_1(dP_t)|, |p_{99}(dP_t)|) \tag{2.3}$$

where p_a denotes the percentile at the a% level. For simplicity, we assume that all CMs set the same margin m_0 for their trades in the presence of non-central clearing. The IM for each position is then calculated as:

$$IM^0_{ij} = m_0|W^0_{ij}|$$

In accordance with the regulations outlined in section 2.2, centrally cleared OTC derivatives positions are assumed to have a holding period of five days, i.e. the CCP would be able to unwind the positions within five days. As such, the IM is scaled by the square root of five for centrally cleared positions:

$$IM_{ij}^0 = m_0\sqrt{5}|W_{ij}^0| \ \forall \ i \in N \text{ and } j = n+1 \tag{2.4}$$

Similarly, non-centrally cleared positions are assumed to have a holding period of ten days due to their increased liquidity risk and smaller netting efficiencies. As such:

$$IM_{ij}^0 = m_0\sqrt{10}|W_{ij}^0| \ \forall \ i,j \in N \tag{2.5}$$

Note that the IM is posted in bilateral transactions only when non-central clearing is enabled. In the alternative configuration without non-central clearing we have:

$$IM_{ij}^0 = 0 \ \forall \ i,j \in N \tag{2.6}$$

Denote $IM_i^0 = \sum_{j=1}^{n+1} IM_{ij}^0$ as the total IM requirements for each CM i at time 0. We subtract the total IM requirements from the CMs' liquid assets under the two different configurations in order to calculate their unencumbered resources. Naturally, since IM_i^0 is higher under non-central clearing, the CMs are more encumbered in this configuration which is the key driver behind our results.

Finally, we calculate the CCP's DF. As stated in section 2.2, the international regulations require systemically important CCPs to be able to withstand the simultaneous default of their two largest CMs under extreme but plausible market conditions. We calculate the uncollateralised losses as follows:

$$SC_i = z\sqrt{5}|W_{ij}^0| - IM_{ij}^0 \ \forall \ i \in N \text{ and } j = n+1 \tag{2.7}$$

where z captures 99.9% of movements:[13]

$$z = \max(|p_{0.1}(dP_t)|, |p_{99.9}(dP_t)|) \tag{2.8}$$

We rank SC_i from largest to smallest and sum the first two entries in order to calculate the DF:

$$DF = SC_{i(1)} + SC_{i(2)} \tag{2.9}$$

Each CM contributes to the DF on a pro-rata basis according to their IM contribution. Denoting individual DF contributions as F_i we have:

$$F_i = \frac{IM_{ij}^0}{\sum_i IM_{ij}^0} DF \; \forall \; i \in N \text{ and } j = n+1 \tag{2.10}$$

This completes the initial system configuration. All positions are assumed to be marked-to-market, i.e. there are no outstanding VM payments as of time 0.

2.3.2 First day effects ($t = 1$)

We begin the stress testing exercise by shocking the asset in order to create mark-to-market gains and losses (VM). We measure the shocks in terms of standard deviations of price changes σ_0. In total we apply four shocks which are measured as multiples of σ_0, $2.33\sigma_0$, $3\sigma_0$, $10\sigma_0$ and $20\sigma_0$.[14] The first two are "mild" shocks and are not expected to stress the system significantly since the IM posted is larger than the VM generated. The latter two are severe shocks with $20\sigma_0$ signifying an extreme market event. We discuss the calibration of these shocks and their interpretation in section 2.4.

[13]Note that this is a conservative approach to size the DF because by using the absolute value of net notional positions in (2.7) we consider the maximum losses that each CM may incur either due to a positive or a negative shock. Alternatively, two separate shocks could be applied to all CMs as different stress scenarios, one positive and one negative, and the DF would be sized as the maximum between the sums of the two largest losses among those scenarios which would result in a slightly smaller DF. This would not have a significant impact on our results given the fact that the normality assumption does not oversize the DF irrespectively of the methodology used.

[14]We also apply negative shocks of corresponding magnitudes. The results are qualitatively and quantitatively similar.

Let ΔP denote the change in the asset's price as a result of the shock. The VM obligation of i to j is calculated as:

$$VM_{ij}^{1} = \max(W_{ij}^{0}\Delta P, 0) \tag{2.11}$$

A positive W_{ij}^{0} signifies i being short and j being long. Hence, a positive (negative) ΔP creates a VM obligation (gain) for i and VM gain (obligation) for j if W_{ij}^{0} is positive and vice versa. Denote $VML_i^1 = \sum_{j=1}^{n+1} VM_{ij}^1$ the total VM requirements for each CM i at time 1. The CMs can pay their VM obligations using their available HQLA AL_i^0 (net of the IM requirements calculated at $t = 0$).

While the study of Heath et al. (2016) assumed static CMs, we allow for portfolio rebalancing by solving an optimisation problem to take into account the fact that the contracts are cleared end-of-day hence some CMs may manage to close out their positions and avoid default.

Denote the updated assets and liabilities of each CM i as A_i^1 and L_i^1. Each CM attempts to close out its positions by minimising the difference between its assets and liabilities. A zero net position would require zero IM $(IM_i^1 = 0)$ and the CM would be able to regain the full amount of IM_i^0 to help repay the VM. Specifically, each CM solves the following optimisation problem:

$$\min_{A_i^1, L_i^1} |A_i^1 - L_i^1| \tag{2.12}$$

subject to:

$$LCR_i^1 = \frac{AL_i^0 - (IM_i^1 - IM_i^0) - VML_i^1}{stress_i} \geq 100\%$$

$$(A_i^1 - L_i^1) - \left(\sum_j X_{ji}^0 - \sum_j X_{ij}^0\right) = RE_i^0$$

where $stress_i$ are the CM's projected net outflows in a stress period for the LCR calculation, R indicates return and E_i^0 is the CM's total equity.

The first condition is the budget constraint stating that the sum of the perceived net IM receipt or payment and the VM obligation must not make the CM's LCR drop to less than 100%. The updated IM (IM_i^1) is a function of the positions A_i^1, L_i^1 and is calculated by updating the matrix $\boldsymbol{X^0}$ and repeating the calculations shown in subsection 2.3.1. We only consider IM gains here because the IM posted remains in the ownership of the CM that posted it. In contrast, VM gains are subject to counterparty risk because it is not certain that they will be delivered by the counterparty. As such, the CMs do not take them into account in their budget constraint, i.e. they do not rely on uncertain VM gains to pay their own obligations.

The second condition states that the CMs expect a small return R on their equity E_i^0 by holding slightly unbalanced portfolios. This reflects their views on the market and we set R to 1 basis point (bp) which signifies the expected daily return. This is included in order to prohibit the CMs from taking unrealistically large net positions which is not reflected in the data. Since the principal operation of the banks in this setup is market making, they tend to hold balanced inventories in order to avoid excessive directional risk. However, CMs that violate their budget constraint still try to achieve zero net positions.

Each CM performs the optimisation by assuming that its counterparties will accept these changes. This implies that the markets are liquid enough to execute these trades. In essence, the IM amounts calculated in (2.12) are the ones they perceive they can achieve, not the realised ones. Defaults occur when we take into account all CMs' optimal values to form the updated exposures matrix and some CMs are unable to deleverage enough to satisfy their constraints. This is much more likely to happen under extreme stress since the VM requirements are larger.

We solve the optimisation for all CMs simultaneously by minimising the sum of the individual objective functions subject to the vectors of budget and return constraints in order to impose the market clearing condition:

$$\sum_i A_i^1 = \sum_i L_i^1 \tag{2.13}$$

Since this is a complete economy, the total values of assets and liabilities in the system remain constant throughout time:

$$\sum_i A_i^1 = \sum_i \sum_j X_{ji}^0$$

$$\sum_i L_i^1 = \sum_i \sum_j X_{ij}^0$$

Once this is achieved, we create the updated bilateral exposures matrix $\boldsymbol{X^1}$ as before using the solutions of (2.12) as the target column and row sums in optimisation (2.1). We calculate the updated matrices $\boldsymbol{G^1}$, $\boldsymbol{N^1}$ and $\boldsymbol{W^1}$ using $\boldsymbol{X^1}$ and calculate the realised IM obligations from $\boldsymbol{W^1}$.

A CM defaults due to liquidity risk if it breaches its LCR requirements. Hence, in order to avoid default the following condition must be satisfied:

$$LCR_i^1 = \frac{AL_i^0 - (IM_i^1 - IM_i^0) - VML_i^1}{stress_i} \geq 100\% \;\forall\; i \in N \tag{2.14}$$

Equation (2.14) captures liquidity risk and is central to our analysis. Since the CMs' available liquidity AL_i^0 is net of the IM posted, it follows that it is lower under non-central clearing due to the increased IM requirements in the bilateral transactions. This then translates into higher liquidity risk under this configuration as there are fewer resources to pay the VM obligations VML_i^1.[15]

A secondary default occurs if a CM that satisfies condition (2.14) does not receive a VM gain due to counterparty default that translates into an equity loss and results in a breach of its CAR minimum requirement of 8%. Denote H the subset of CMs defaulting due to their inability to satisfy (2.14). Hence, an additional condition for liquid CMs not belonging in this subset to avoid default is:

$$CAR_i^1 = \frac{E_i^0 - \sum_h \max(VM_{hi}^1 - IM_{hi}^0, 0)}{RWA_i} \geq 8\% \;\; \forall\; i \in N \backslash H \text{ and } h \in H \tag{2.15}$$

where RWA_i is the CM's risk weighted assets used for the calculation of CAR.

Equation (2.15) captures counterparty risk. If non-central clearing is disabled then $IM_{hi}^0 = 0$ and the CMs translate the whole missed VM receipt as an equity loss. In the alternative configuration, the IM protects the CMs to an extent which is the reasoning

[15] For completeness we also considered market risk, i.e. the revaluation of positions as a source of risk. However, it has a negligible effect on our results and is not relevant to our analysis, hence we do not report it.

behind the introduction of non-central clearing. Denote D the subset of all CMs that default at $t = 1$ by failing to satisfy any of conditions (2.14) and (2.15). We assume that CMs that default due to counterparty risk, i.e. due to violation of (2.15) repay their VM obligations since they have sufficient liquid resources to do so.

The liquid resources available to surviving CMs at the end of $t = 1$ are:

$$AL_i^1 = AL_i^0 - (IM_i^1 - IM_i^0) - (VML_i^1 - VMG_i^1) \; \forall \, i \in N \backslash D \tag{2.16}$$

where VMG_i^1 denotes the realised VM gains for CM i.

Similarly, the equity available to surviving CMs at the end of $t = 1$ is:

$$E_i^1 = E_i^0 - \sum_h \max(VM_{hi}^1 - IM_{hi}^0, 0) \; \forall \, i \in N \backslash D \text{ and } h \in H \tag{2.17}$$

We measure systemic risk (SR_1) as the total equity loss in the system:

$$SR_1 = \sum_i (E_i^1 - E_i^0) \; \forall \, i \in N \tag{2.18}$$

In contrast to the CMs, the CCP does not translate uncollateralised losses into equity losses but it manages them in accordance with its DMP which is modelled next.

While technically this is a zero-sum game as a CM's devaluation of its assets corresponds to an equal reduction of the defaulted counterparty's liabilities, it is important to consider those losses as part of the overall social welfare. Systemic risk poses an externality because failing banks may require ex-post bailouts and equity losses lead to undercapitalisation of the financial system with adverse consequences for the real economy (Acharya et al. (2017), Brunnermeier and Cheridito (2019)).

2.3.3 Second day effects $(t = 2)$

At $t = 2$ the CCP manages the defaulting portfolios and uncollateralised losses it sustains at $t = 1$, if any. If there are no defaults on the first day, there are no further losses in the system and the stress testing exercise stops there.

We assume that on the second day the CCP performs a margin update, i.e. it updates its IM requirements upwards to take into account the increased volatility of the market. This effect is known as margin procyclicality and is a standard practice of CCPs which may have negative consequences for systemic stability given that margins act as destabilising factors in illiquid markets (Brunnermeier and Pedersen, 2009). If the shock is large enough to be considered a tail scenario by the VaR model, the IM increases exerting further liquidity pressure on CMs. Margin procyclicality is a major concern for regulators who plan to incorporate it into stress testing methodologies considering the increasing importance of CCPs in derivatives markets (BoE, 2015). Empirically, some papers have documented that CCPs quickly raise margins following a shock but are slower in lowering them after volatility declines (Abruzzo and Park, 2016), while others have found limited evidence for procyclicality (Lewandowska and Glaser, 2017). However, the market turmoil of March 2020 has renewed interest in margin procyclicality among policymakers (FSB, 2020b).

Following the default of at least one CM, the CCP becomes the owner of its centrally cleared portfolio. Its first act is to offload the portfolio from its books in order to become market neutral again and avoid potential future VM obligations to the counterparties. As explained in section 2.2, the main tool at the CCP's disposal in order to achieve this is the auction.

The clearing rules specify the set-up of the auction (see e.g. section 9 ICEU (2017) and Ferrara et al. (2017)). It is a first-price sealed bid auction where all CMs are obligated to participate. The CMs have the right to bid negatively, i.e. request resources from the CCP in order to obtain the defaulting portfolio (for example because it consists of net short positions and the CMs request the premium or due to its excessive riskiness). As mentioned before, the CCP incentivises CMs to bid sensibly by allocating uncollateralised losses according to the bidding behaviour. This implies the existence of a loss function in the payoff of the bidders in contrast to the standard auction setting where losers walk away with nothing.

We adopt the standard auction setting where the bidders are risk-neutral (Milgrom and Weber, 1982). For simplicity, the CCP is assumed to combine all defaulting portfolios together in case of multiple defaults and auctions it off as one item. The total value of this portfolio (PV) is:

$$PV = \sum_d \sum_j (X^1_{jd} - X^1_{dj})s \ \forall \ d \in D \text{ and } j \in N \tag{2.19}$$

which is the sum of the total assets minus total liabilities of centrally cleared positions as captured by the clearing fraction s of defaulted CMs belonging in the subset D.

Since the CCP marks-to-market the portfolio, its price is known to be PV. However, the incorporation of the defaulting portfolio into each CM's existing one creates unique new IM gains or losses which differentiate each bidder's valuation. Each surviving CM's IM posted to the CCP at the end of $t = 1$ was:

$$IM^1_{ij} = m_0\sqrt{5}|W^1_{ij}| \ \forall \ i \in N \backslash D \text{ and } j = n+1$$

Let $WD = \sum_d W^1_{dj} \ \forall \ d \in D$ and $j = n+1$ denote the net notional of the defaulting portfolio. The net IM gain or loss from incorporating the defaulting portfolio into each CM's existing one is calculated as:

$$IM^2_{ij} - IM^1_{ij} = m_1\sqrt{5}|W^1_{ij} + WD| - m_0\sqrt{5}|W^1_{ij}| \ \forall \ i \in N \backslash D \text{ and } j = n+1 \tag{2.20}$$

where m_1 is the updated VaR estimated as in (2.3) but including the change in the asset price ΔP due to the shock into the Monte Carlo paths to capture margin procyclicality.

The fair private value of each CM for the defaulting portfolio is thus given as:

$$u_i = PV - (IM^2_{ij} - IM^1_{ij}) \ \forall \ i \in N \backslash D \text{ and } j = n+1 \tag{2.21}$$

Note that PV is constant and known to all CMs since the CCP marks-to-market the portfolio which makes this auction a private value auction. A positive (negative) PV implies an asset (liability) for the CM, hence it posts (requests) compensation to (from) the CCP to acquire the portfolio. A positive (negative) net IM $(IM^2_{ij} - IM^1_{ij})$ is a future payment (receipt) to (from) the CCP hence the CM requests (posts) this amount from (to) the CCP.

As in the standard auction setting, we assume that the CMs' valuations u_i are independent and drawn from a known to all distribution F with density f and support $[\underline{u}, \overline{u}]$. We assume a uniform distribution with support $\underline{u} = -0.1$ and $\overline{u} = 0.1$ in \$ trillion.[16]

Each CM places a bid $b_i = b(u_i)$. In a standard setting the payoff π_i would be:

$$\pi_i = \begin{cases} u_i - b_i \text{ if } b_i > \max_{j \neq i} b_j \\ 0 \text{ otherwise} \end{cases}$$

That is, the winner places the highest bid and profits the difference between his valuation and his bid while losers walk away with nothing, i.e. zero payoff.

However, in this case the CCP punishes losers by requesting contributions via the Powers of Assessment according to the ranking of the bids. The contributions are capped to a multiple of the original DF contribution, typically two. CMs cannot calculate the loss function ex-ante (except for the maximum exposure due to the cap) for several reasons.

First, it requires the ordering of the bids to be known which is obviously not possible before the auction is complete. Second, the bids are sealed so only the CCP knows the ranking ex-post. Third, the CMs are not aware of the total losses faced by the CCP, nor the individual contributions to the DF from all the CMs. Hence, we depart from the usual notion of risk estimation to model CMs that face Knightian uncertainty, i.e. an unmeasurable risk.

Under such a setting, agents are said to be Knightian uncertainty averse and maximise expected utility given the least favourable state of nature. In other words, they maximise expected utility under the worst-case scenario according to the maximin expected payoff representation introduced by Gilboa and Schmeidler (1989). However, the worst-case scenario is known to everyone: it is the one where the losses are so large that the CMs pay the capped amount which is equal to twice their original DF contribution irrespectively of the bidding order. That is, the losses are not fully covered by the addition of twice the original DF to the available resources.

In Appendix A.1 we prove that in this case the loss function becomes irrelevant and the auction boils down to the standard independent private value (IPV) case where the

[16]The uniform distribution is the standard assumption in the auction theory literature. Selecting broader bounds results in lower overall bids while tighter bounds increase them. Alternative bounds do not have a significant effect on our results.

bid function is given by:

$$b(u_i) = \begin{cases} \frac{(M-1)\int_{\underline{u}}^{u_i} x_i F(x_i)^{M-2} f(x_i) dx_i}{F(u_i)^{M-1}} \text{ if } \underline{u} < u_i \leq \overline{u} \\ -\infty \text{ if } u_i = \underline{u} \end{cases} \tag{2.22}$$

where M is the number of bidders, i.e. the number of surviving CMs. A CM whose valuation coincides with the lower bound of the distribution $\underline{u}$ would be a certain loser and ask an infinite amount of compensation from the CCP. Our bounds are broad enough to never observe this case.

Since the CMs have a finite amount of liquid resources available, they bid in accordance to their budget constraint (Che and Gale, 1998):

$$b^*(u_i) = \min(b(u_i), AL_i^1) \tag{2.23}$$

Once all bids (2.23) have been placed, the CCP assigns the portfolio to the highest bidder. If the highest bid is negative, the CCP is assumed to always be able to pay the winner.[17]

Next, if the CCP faces uncollateralised losses that exceed the defaulted CMs' IM and DF contributions as well as a small equity tranche of \$100 million, it calls on its Powers of Assessment. Each surviving CM is obligated to contribute up to twice its original DF amount starting from the lowest bidder and ascending until the losses have been covered or every CM has pledged the capped amount and the losses are still not fully covered. The CMs use their remaining liquid assets to pay the additional funds. If any CM does not have enough liquid resources, i.e. it breaches its LCR requirements, it defaults due to liquidity stress. Hence, the following condition must hold in order to avoid default:

$$LCR_i^2 = \frac{AL_i^1 - PA_i}{stress_i} \geq 100\% \;\; \forall\, i \in N \backslash D \tag{2.24}$$

where PA_i is the amount asked by the CCP under the Powers of Assessment.

In the most extreme case when there are still unfunded losses after the Powers of

[17] In reality, it may occur that the CCP does not have enough resources of its own to pay the bid in which case it has to rely on its DF and then its Powers of Assessment to replenish it. This adds an additional layer of complexity and also introduces the possibility of CCP default hence we eschew it.

Assessment, the CCP assigns these residual losses via VMGH to the winning counterparties. This haircut is applied pro-rata and is directly translated into an equity loss for the CMs since the CCP does not post IM to them. Any CM whose updated CAR drops below 8% defaults due to counterparty risk. In other words, the following condition must hold to avoid default:

$$CAR_i^2 = \frac{E_i^1 - VM_{ji}^2}{RWA_i} \geq 8\% \;\; \forall\, i \in N \backslash D \text{ and } j = n+1 \tag{2.25}$$

where VM_{ji}^2 is the VM loss due to VMGH.

We measure systemic risk for $t = 2$ (SR_2) as:

$$SR_2 = \sum_i (E_i^2 - E_i^1) \;\forall\, i \in N \backslash D \tag{2.26}$$

The total equity loss (SR_T) in the system is:

$$SR_T = SR_1 + SR_2 \tag{2.27}$$

which gives the total measure of systemic risk.

Any CMs that default at $t = 2$ would require the repetition of the auction process, although there are no uncollateralised losses in this case. We do not perform this step as it does not add substantial information to our analysis.

2.3.4 Model implications

The model has several implications for the redistribution of risks across the CCP and the CMs following the introduction of non-central clearing. First, the model predicts that the liquidity risk of the CMs will increase because they have fewer unencumbered liquid assets to pay their VM obligations, as captured by equation (2.14). Second, it is also expected that their counterparty risk will decrease as the presence of the IM in the bilateral transactions will protect them from losses due to counterparty default, as seen in equation (2.15). Third, holding the CCP's resources constant, non-central clearing can increase the CCP's losses if more CMs default on their obligations due to liquidity risk. Hence, the effect on systemic risk is ambiguous as the collateralisation of bilateral transactions can reduce losses due to default but can lead to higher losses for the CCP which will be subsequently mutualised across the surviving CMs.

We finish this section by highlighting certain model simplifications and abstractions from real life. First, due to data limitations we do not include non-banks or non-financial institutions (end-users). These entities are more likely to lie in the periphery of the network although their significant presence in the OTC interest rate derivatives market is recognised (ISDA, 2014a). However, non-banks tend to be more susceptible to liquidity shocks (Paddrik et al., 2020), which would only reinforce our results on the prevalence of liquidity risk in cleared derivatives markets. Second, the available aggregate data do not allow for the correct identification of connections. While we simulate 100 random networks in order to average out the results, there remains the possibility of considerable model error. Nonetheless, we base our network formation on existing literature which is based on actual data of bilateral exposures. Third, we do not account for banks' additional sources to raise liquidity such as the repo market. Equally however, systemic events are characterised by multiple market failures as was evident in the recent financial crisis and their orderly operation cannot be guaranteed (Gorton and Metrick, 2012). While macroprudential stress test models add general equilibrium dimensions to improve on their microprudential counterparts, there is a limit to the degree of generalisation that is possible without losing tractability (Demekas, 2015). Stress testing models remain partial equilibrium exercises but they can be extended in order to balance the trade-off between reality and model tractability.

2.4 Data

We test the model implications by running simulations using data on 39 banks that act as CMs. The selection of these banks is based on a study by the Macroeconomic Assessment Group on Derivatives (MAGD), also adopted by Heath et al. (2016), which uses proprietary data and simulates a core-periphery structure of the OTC derivatives network that comprises the 16 largest global derivatives dealers forming the densely connected core and a number of smaller banks representing individual jurisdictions forming the sparsely connected periphery (MAGD, 2013). The list of banks is provided in Table A.1 in Appendix

A.2.

We obtain the following data for the banks from their 2018 annual reports: total interest rate derivatives gross assets and liabilities, gross notional, liquid assets as measured by their HQLA required under Basel III regulation and used among others for derivatives activities, as well as their total equity (Tier 1 plus Tier 2 capital). The annual reports include data for five major derivatives asset classes, those being equity, currency, commodity, credit and interest rate. For simplicity, in this study we focus on one asset class and we choose the interest rate one since it dominates all other classes in terms of notional and exposures. In this way we capture more than 85% of the total OTC derivatives markets activity in terms of gross notional which stood at $544 trillion at the end of 2018 (BIS, 2019). We set the central clearing fraction s equal to 75% in line with current estimates for interest rate derivatives (BIS, 2019), with the rest 25% of trading activity being bilaterally traded.

A summary of the data is given in Table 2.2. Figures are in $ trillion. The majority of trading activity is concentrated in the Core-16 banks, accounting for approximately 80% of total assets, liabilities and notional, with the rest 20% shared among the Periphery-23 banks. Approximately 50% of total liquid assets are in the core and the rest 50% in the periphery, while 57% of total equity belongs to the Core-16 banks and 43% in the Periphery-23 banks. The derivatives data represent the aggregates for each bank which we use to infer the unobservable bilateral connections as explained in the previous section. Using this data to calibrate our model, the CCP collects $224.3 billion in IM and $13.1 billion for its default fund, approximately twice as much as the resources collected by LCH, the leading CCP for interest rate swaps.[18] When non-central clearing is enabled, CMs post $449 billion in IM between themselves. The fact that the CMs post almost twice as much IM in the bilateral transactions (covering 25% of total notional) compared to the centrally cleared ones (covering 75% of total notional) highlights the netting benefits arising from the dominance of CCPs.

Regarding the volatility parameter σ_0, since we don't have any prior knowledge of its value we refer to the study of MAGD (2013) which estimates the daily volatility of

[18] According to the 2017 EU-wide CCP stress test published by the European Securities and Markets Authority, LCH had approximately EUR 110 billion in IM and EUR 7 billion in its default fund (ESMA, 2018).

Table 2.2: Data summary ($ trillion)

	Total	**Core-16**	**Periphery-23**
Gross assets	2.78	2.22	0.56
Gross liabilities	2.66	2.07	0.59
Gross notional	465.40	386.32	79.08
Liquid assets	8.76	4.44	4.32
Equity	3.19	1.81	1.38

Source: Annual reports and own calculations

the interest rate derivatives class using proprietary data equal to 0.068%.[19] We use this parameter value to calculate the market shocks which we interpret as parallel movements of the swap curve used to price interest rate swaps, the dominant contract of interest rate derivatives.

To give context to the magnitude of the shocks we apply to the system, a $2.33\sigma_0 \approx 15.8$ bps movement is approximately one-third the shock to the USD Libor swap rate on the day Lehman Brothers defaulted, which was 45 bps according to a report by the Commodity Futures Trading Commission (CFTC, 2019). A $3\sigma_0 \approx 20.4$ bps movement is equivalent to approximately one-half the Lehman shock, a $10\sigma_0 \approx 60.8$ bps movement is 1.5 times the Lehman shock, while a $20\sigma_0 \approx 136$ bps movement is 3 times the Lehman shock. Hence, a $10\sigma_0$ shock can be described as "extreme but plausible" while a $20\sigma_0$ is probably beyond what CCPs would consider plausible. The reason we apply such a shock is because we can simulate an extreme scenario where the CCP's pre-funded resources are depleted, which has happened in rare cases historically. Given that our CCP is a global market representative, the shock required to exhaust its resources is also very large. With smaller and more realistic CCPs the corresponding shock would be smaller.

[19] While a different value of σ_0 would change our absolute results, we are more interested in the relative results, i.e. comparing before and after the introduction of non-central clearing, and we expect those to be robust to different parameter values.

2.5 Empirical results

2.5.1 Baseline analysis

We report the baseline model results for each of the two rounds (days 1 and 2) in Table 2.3. The table presents mean values across the 100 simulated networks for the defaults due to liquidity and counterparty risk as well as the overall systemic and CCP losses. The results derived from the simulations are compared between the two configurations, with and without non-central clearing (NCC), for shocks of various magnitudes. We calculate the % change of effects achieved through NCC and assess the statistical significance through a two-sample *t*-test.[20] The results are also graphically presented in bar graphs in Figures 2.1 and 2.2 for ease of exposition.

[20] We also apply the Welch's *t*-test to control for unequal variances between the two samples. The results remain the same.

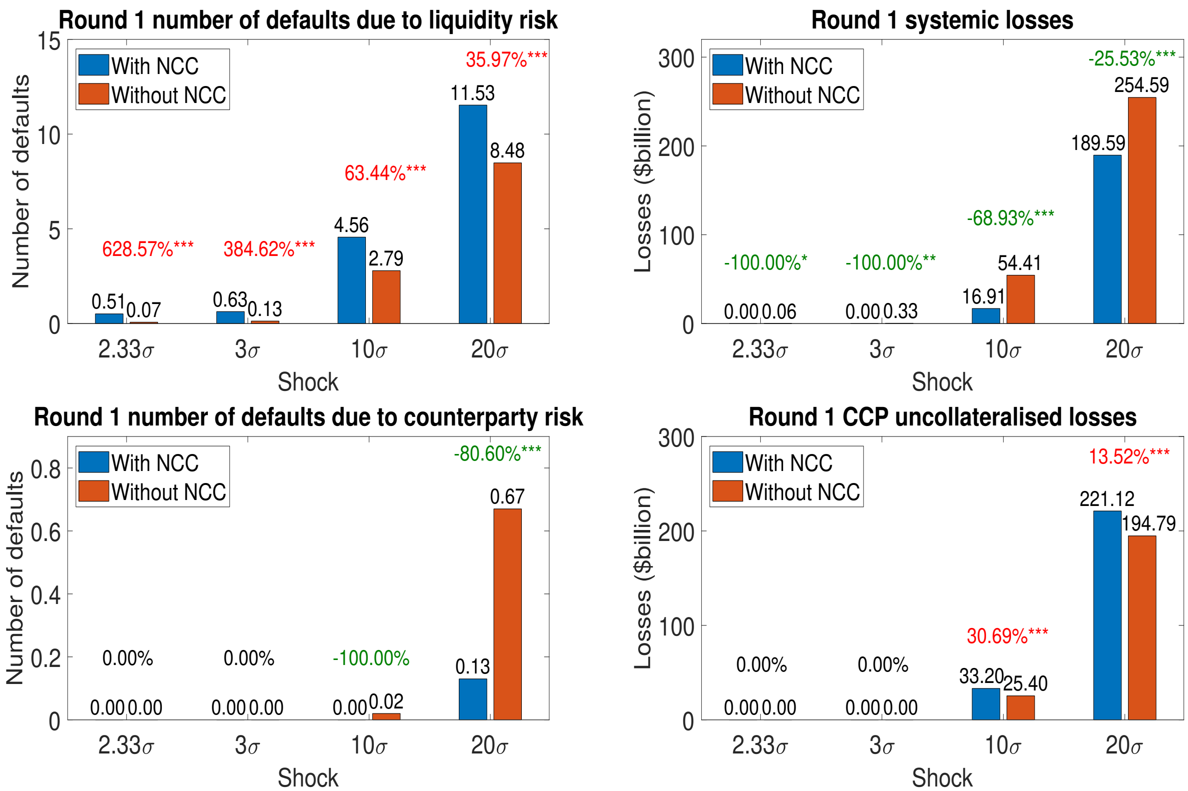

Figure 2.1: Baseline configuration results (first day)

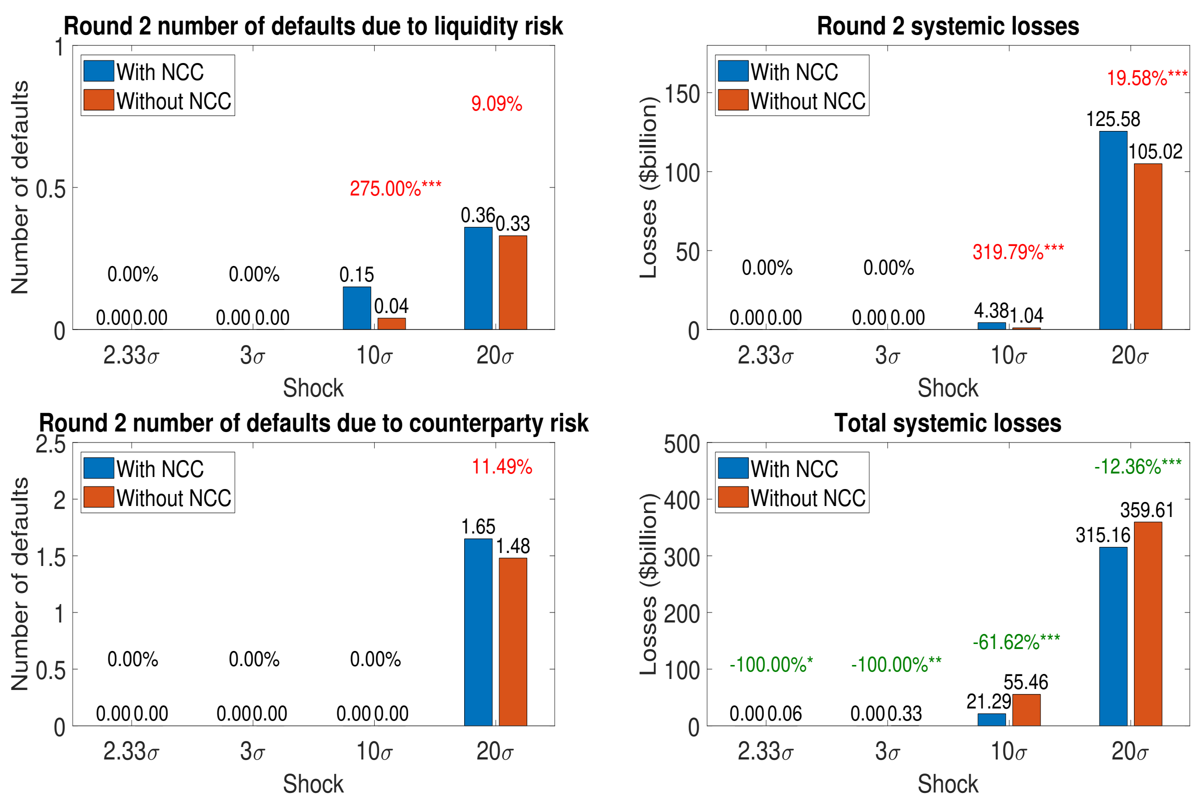

Figure 2.2: Baseline configuration results (second day)

Table 2.3: Baseline configuration results

This table reports the baseline results of the analysis. The CCP is assumed to clear 75% of all derivatives transactions, and the banks default due to liquidity risk if their LCR drops to less than 100% and due to counterparty risk if their CAR drops to less than 8%. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	Shock	With NCC	Without NCC	% Change
Panel A: Day 1 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.51	0.07	628.57^{***}
	$3\sigma_0$	0.63	0.13	384.62^{***}
	$10\sigma_0$	4.56	2.79	63.44^{***}
	$20\sigma_0$	11.53	8.48	35.97^{***}
Systemic losses ($ billion)	$2.33\sigma_0$	0.00	0.06	-100.00^{*}
	$3\sigma_0$	0.00	0.33	-100.00^{**}
	$10\sigma_0$	16.91	54.41	-68.93^{***}
	$20\sigma_0$	189.59	254.59	-25.53^{***}
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.02	-100.00
	$20\sigma_0$	0.13	0.67	-80.60^{***}
CCP uncollateralised losses ($ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	33.20	25.40	30.69^{***}
	$20\sigma_0$	221.12	194.79	13.52^{***}
Panel B: Day 2 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.15	0.04	275.00^{***}
	$20\sigma_0$	0.36	0.33	9.09
Systemic losses ($ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	4.38	1.04	319.79^{***}
	$20\sigma_0$	125.58	105.02	19.58^{***}
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	1.65	1.48	11.49
Panel C: Days 1&2 results				
Systemic losses ($ billion)	$2.33\sigma_0$	0.00	0.06	-100.00^{*}
	$3\sigma_0$	0.00	0.33	-100.00^{**}
	$10\sigma_0$	21.29	55.46	-61.62^{***}
	$20\sigma_0$	315.16	359.61	-12.36^{***}

2.5.1.1 First day defaults and losses $(t = 1)$

The results from day 1 for shocks ranging from 2.33 to 20 standard deviations are reported in Panel A of Table 2.3. Defaults due to liquidity risk occur due to the violation of condition (2.14), that is, if the net IM and the VM obligations make the banks breach their LCR requirement. The introduction of NCC significantly increases the liquidity-driven default frequency for all market shocks due to the higher liquidity encumberment of the banks, with the increase being most pronounced for mild shocks (628.57% at $2.33\sigma_0$) and least pronounced during extreme market stress (35.97% at $20\sigma_0$). This is because when large market shocks occur many banks cannot repay their VM obligations even in the absence of the liquidity encumberment caused by the introduction of NCC. In absolute terms, the number of defaults is substantial, reaching an average of 11.53 under NCC and 8.48 without in the most extreme case. The results indicate that NCC leads to a significant increase in liquidity risk which affects a large number of banks.

The day 1 systemic equity losses defined in (2.18) caused by the defaults due to liquidity risk are discussed next. For mild shocks NCC eliminates all systemic losses due to the added protection offered by the IM in the bilateral transactions. As the shock magnitude increases, the crystallised losses become larger as expected, and NCC decreases the overall losses. The loss reduction is both statistically and economically significant. Specifically, NCC caps the overall systemic losses at \$189.59 billion or 5.94% of the total equity of all banks. Without NCC the losses are as high as \$254.59 billion or 7.97% of total equity, an increase of 25.53% or \$65 billion. Even though the number of defaults due to liquidity risk is higher under NCC in extreme market conditions, leading to higher raw losses before taking into account the collateral, the IM posted in bilateral transactions protects the surviving participants. Our findings provide support for the role of NCC as a mechanism for obtaining economically significant savings in systemic losses attributed to extreme market shocks in the OTC derivatives markets.

Even though NCC significantly reduces systemic losses, the reduction of defaults due to counterparty risk as a result of these losses is more limited. This is because defaults due to counterparty risk are zero or near zero with or without NCC in all but the most extreme market shock case. The banks have sufficient capital to withstand the losses that occur, and while under a $20\sigma_0$ scenario there is a statistically significant reduction of defaults of 80.60%, the actual number of defaults is very small, 0.13 under NCC and 0.67 without. This finding corroborates Cont (2017) who argues that liquidity risk is the main source of stress in cleared markets. It also shows that the small benefits of introducing NCC in terms of decreasing counterparty risk are overshadowed by the accompanying increase of liquidity risk which adds to the evidence for the effect of risk transformation.

The CCP sustains zero uncollateralised losses under mild stress since its resources remain constant under both configurations and are sufficient to cover losses due to default. However, due to the dominance of the CCP in our model which clears 75% of total trading activity, the uncollateralised losses in the most extreme scenario are very large, standing at \$221.12 billion under NCC and \$194.79 billion without. NCC increases the losses sustained by the CCP by 13.52% in the most extreme case because of the higher number of defaults due to liquidity risk. Nonetheless, since some of those losses are owed to other defaulted counterparties, we assume that the CCP is only liable to repay surviving CMs. As such, the magnitude of losses presented in Table 2.3 overestimates the true level of stress imposed on the CCP.

While NCC appears effective at reducing counterparty and systemic risks when considering the first-round results, the increased liquidity risk in the most extreme shock scenario leads to a higher number of total defaults, so the CCP sustains larger losses in this case. This has important implications for financial stability because these losses are transmitted back to the surviving CMs in accordance with the DMP as reported in the ensuing analysis.

2.5.1.2 Second day defaults and losses $(t = 2)$

On the second day, the CCP distributes any losses in excess of the defaulted CMs' posted IM and DF contributions and a small tranche of its own equity to the surviving CMs. The results are presented in Panel B of Table 2.3.

Defaults due to liquidity risk (i.e. due to insufficient liquid assets to meet the Powers of Assessment (2.24)) and counterparty risk (i.e. due to equity losses caused by VMGH (2.25)) only occur under severe stress when the CCP's pre-funded resources are depleted and the recovery tools are activated. The defaults due to liquidity risk remain small with and without NCC, reaching 0.36 and 0.33 on average respectively, due to the cap on the amount of resources that the CCP can ask for. As such, we do not find that the CCP poses a substantial liquidity risk to its members, alleviating concerns about the repercussions of the stress imposed on CMs due to the Powers of Assessment (Domanski et al., 2015).

The equity losses sustained by CMs due to VMGH defined in (2.26) reach \$125.58 billion under NCC or 4.18% of remaining total equity from day 1 and \$105.02 billion without or 3.57% of remaining equity in the most extreme market scenario. Interestingly, the introduction of NCC seems to amplify the CCP's potential for contagion in the most extreme market conditions, increasing average losses by \$20.56 billion or, equivalently, by 19.58%. The increased liquidity risk leads to more initial defaults and more uncollateralised losses for the CCP, which transmits them back to the surviving CMs leading to higher secondary losses. As such, the CCP's propensity to act as a source of contagion in the most extreme cases is amplified with the introduction of NCC. Nonetheless, the increase in losses transmitted by the CCP is not enough to significantly increase the number of defaults occurring due to counterparty risk, implying that the CMs are able to withstand the additional losses distributed by the CCP under NCC. The number of defaults due to counterparty risk is virtually zero for all shocks except the most extreme one, where they average 1.65 under NCC and 1.48 without, statistically the same.

2.5.1.3 Overall systemic losses

We report the overall systemic losses that occur over the two days of the clearing process derived using (2.27) in Panel C of Table 2.3.

NCC significantly reduces overall systemic losses under all market conditions. Under NCC, losses remain zero for small to moderate shocks, rising to \$21.29 billion or 0.67% of total initial equity for a $10\sigma_0$ shock and \$315.16 billion for the most extreme $20\sigma_0$ shock or 9.87% of total initial equity. Without NCC, losses occur in all cases, rising to \$55.46 billion or 1.74% of total initial equity for a $10\sigma_0$ shock and \$359.61 billion or 11.26% of total initial equity for a $20\sigma_0$ shock. The findings suggest that the introduction of NCC reduces losses by 61.62% and 12.36%, respectively for shock sizes of $10\sigma_0$ and $20\sigma_0$, which amounts to economically significant savings of \$34.17 billion and \$44.45 billion or 1.07% and 1.39% of total initial equity respectively.

We can thus deduce that the introduction of NCC promotes financial stability in terms of reducing total equity losses. The exchange of IM in bilateral transactions mitigates the losses arising from counterparty risk at the expense of an increase of liquidity risk. However, this increase has implications for the stability of the CCP since it faces larger losses in adverse market conditions and as a result the knock-on effects are also more severe. We further analyse the implications of the expansion of central clearing for systemic risk in the next subsection.

2.5.2 Central clearing and systemic risk

In this subsection we examine the impact of the expansion of central clearing on systemic risk. Post-crisis regulations have heavily promoted the expansion of CCPs as a result of them being regarded as bulwarks that provide stability to the financial system, and the introduction of non-central clearing is an additional step towards that goal by incentivising market participants to switch to central clearing in order to benefit from lower margin costs (BCBS-IOSCO, 2015).

We repeat the stress testing exercise twice by setting the clearing fraction s equal to 0.5 and 0.95, i.e. we assume that 50% and 95% of positions are centrally cleared compared to 75% in the earlier configuration. That is, we consider a scenario with reduced central clearing and another one with increased central clearing compared to the earlier configuration. For each repetition a new set of 100 random adjacency matrices is generated. The results are presented in Table 2.4 as well as graphically in Figures 2.3 - 2.6.

On day 1, liquidity risk remains the main source of stress but the corresponding number of defaults decreases with the expansion of the CCP because the increasing netting benefits lower the exposures and the amount of collateral required so the CMs have lower liquidity encumberment. When the CCP clears 50% of transactions, the number of liquidity-driven defaults is 17.91 and 11.28 with and without NCC respectively, compared to 6.20 and 5.83 when 95% of transactions are centrally cleared. In addition, because of the decreasing role of non-central clearing, which affects only 5% of transactions in the increased central clearing configuration, the % increase in the number of defaults is lower when the CCP is dominant.

The decrease in the number of defaults due to liquidity risk leads to a sizeable decrease in systemic losses on day 1. With decreased central clearing, the losses in the most extreme market scenario under NCC are $528.76 billion or 16.55% of total equity while with increased central clearing they are $23.55 billion or 0.74% of total equity, reduced by 95.54%. Without NCC the corresponding losses are $664.06 billion or 20.79% of total equity and $36.30 billion or 1.14% of total equity, reduced by 94.53%. These results illustrate the very significant reduction of exposures and counterparty risk due to market shocks that can be achieved with the proliferation of CCPs. NCC reduces these losses even further which corroborates our baseline results from subsection 2.5.1.

Defaults due to counterparty risk are completely eliminated with a clearing fraction of 95% as fewer CMs default on their VM obligations due to liquidity risk, leading to smaller systemic losses and hence zero defaults due to counterparty risk, with or without NCC. Under reduced central clearing, the number of defaults due to counterparty risk is reduced with NCC but similarly with the baseline results they are low, 1.44 and 2.89 with and without NCC respectively. This shows that even with very large equity losses of up to 20% of total capital most banks do not breach their capital adequacy ratios.

On the other hand, the expansion of central clearing also increases the systemic importance of the CCP and its propensity for contagion under severe stress. The uncollateralised losses faced by the CCP in the most extreme market scenario with 50% of positions centrally cleared are $166.70 billion under NCC and $147.16 billion without, compared to $201.30 billion and $193.62 billion respectively with 95% of positions centrally cleared. Interestingly, even though the number of CMs that default on their VM obligations due to liquidity stress decreases, the losses incurred by the CCP increase as it expands its operations. This highlights the fact that in a configuration where the CCP is most dominant, the exposures that manifest when shocks occur are so large that only a small number of defaults is sufficient to generate losses comparable to those in a configuration with a smaller CCP.

The number of defaults due to liquidity risk on day 2 is further reduced with the expansion of central clearing to 0.10 and 0.12 with and without NCC respectively since the CMs are less liquidity encumbered which allows them to meet their Powers of Assessment obligations.

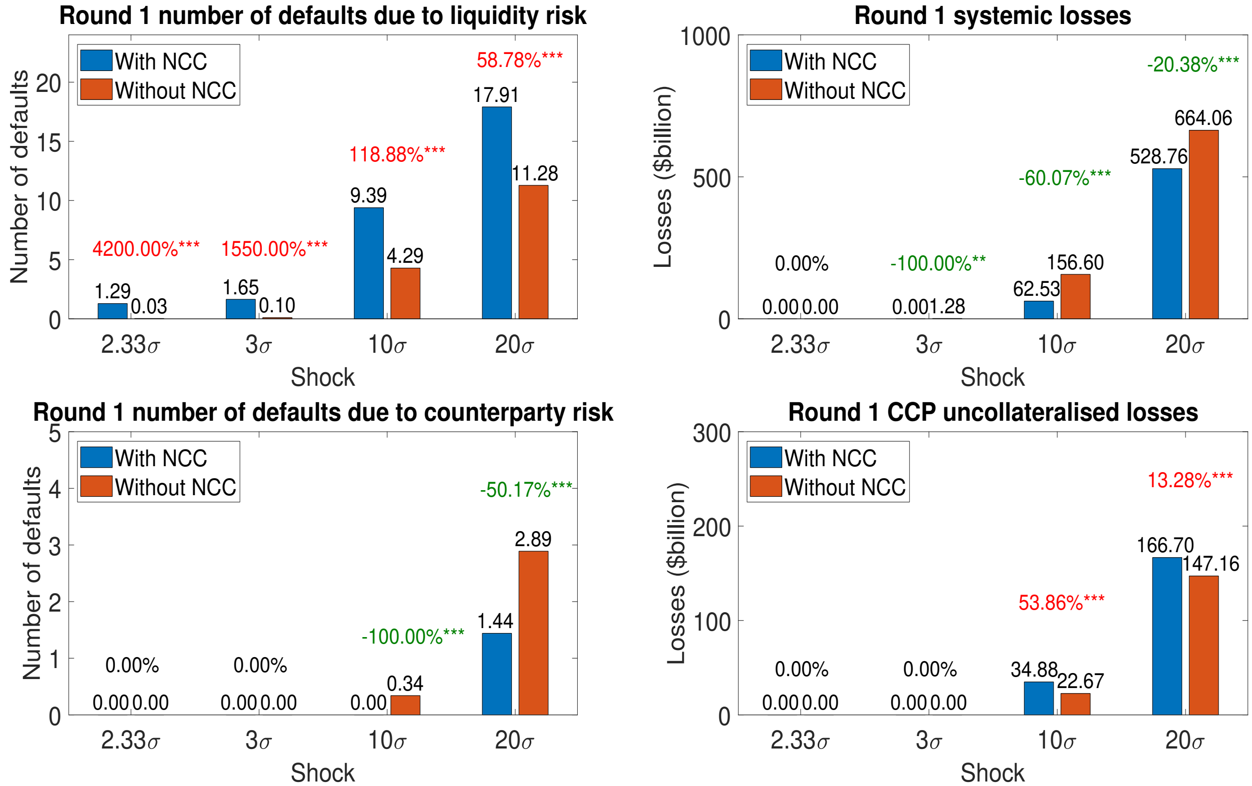

Figure 2.3: Alternative central clearing configurations results - Reduced central clearing (first day)

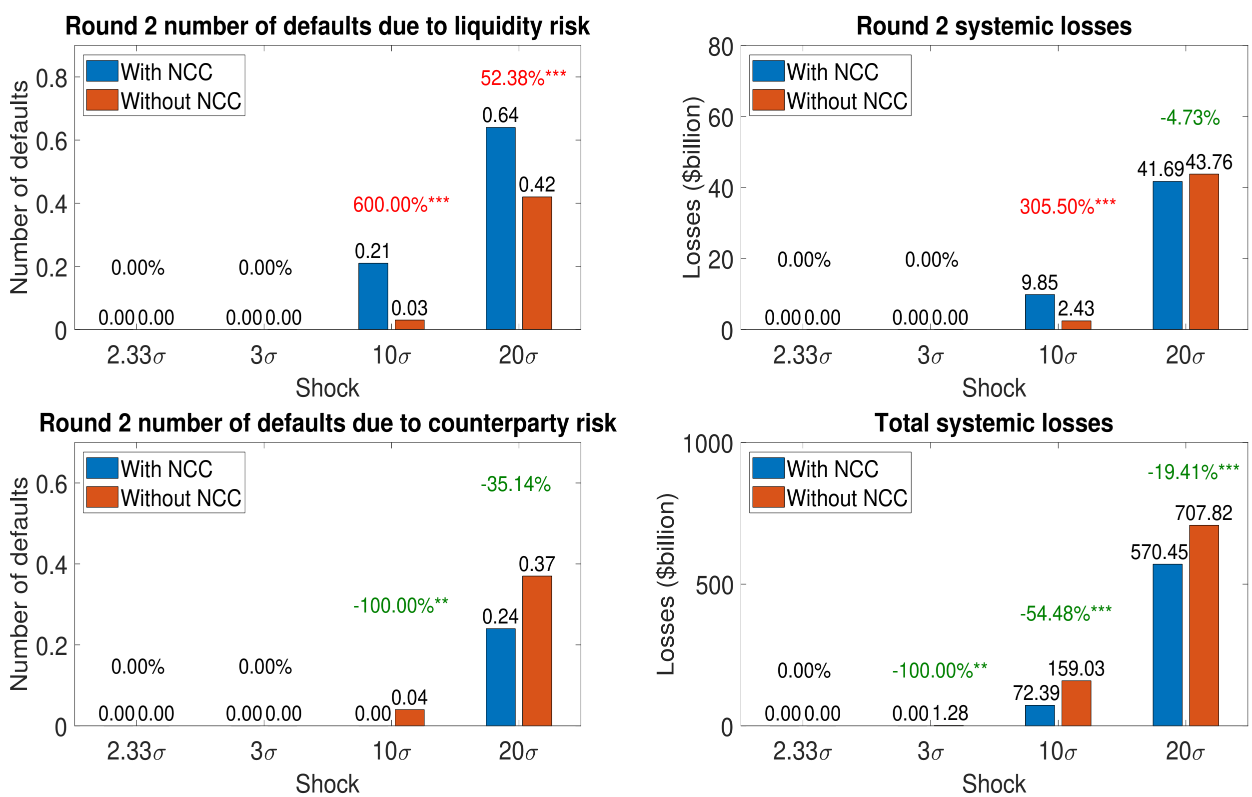

Figure 2.4: Alternative central clearing configurations results - Reduced central clearing (second day)

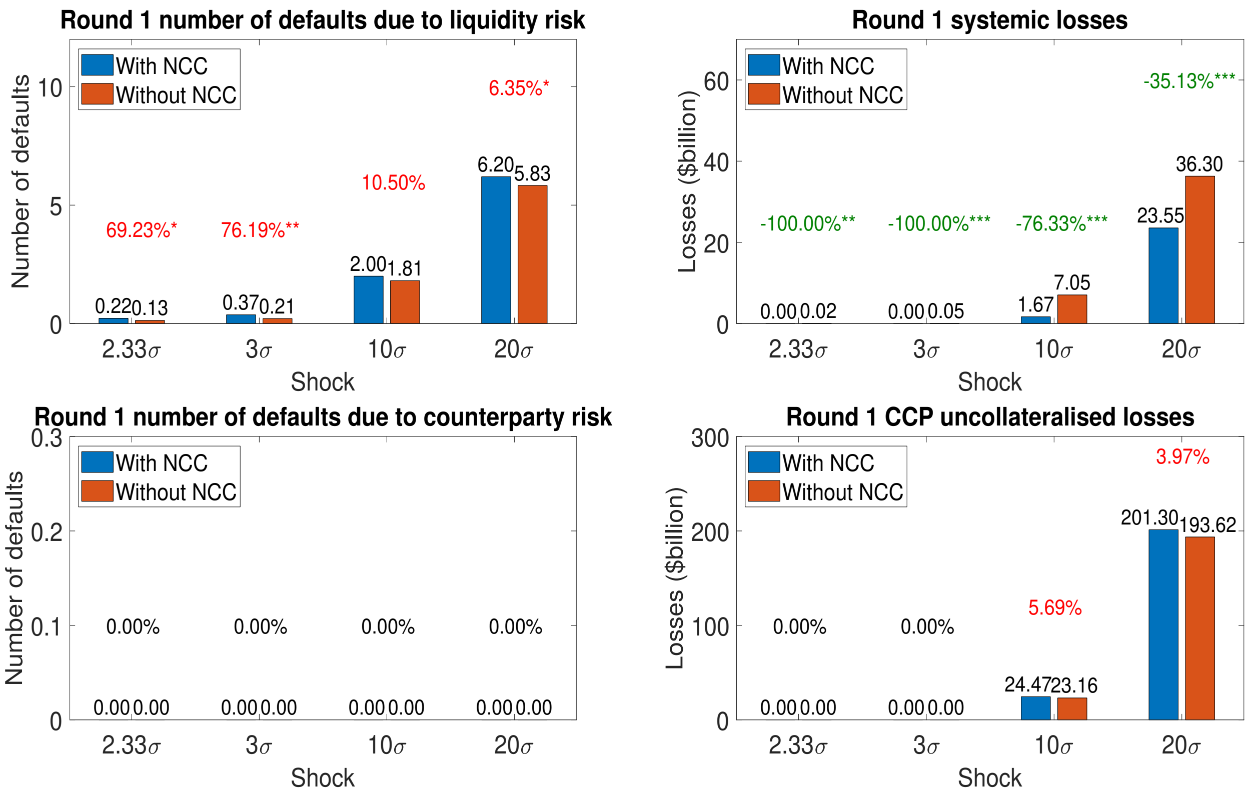

Figure 2.5: Alternative central clearing configurations results - Increased central clearing (first day)

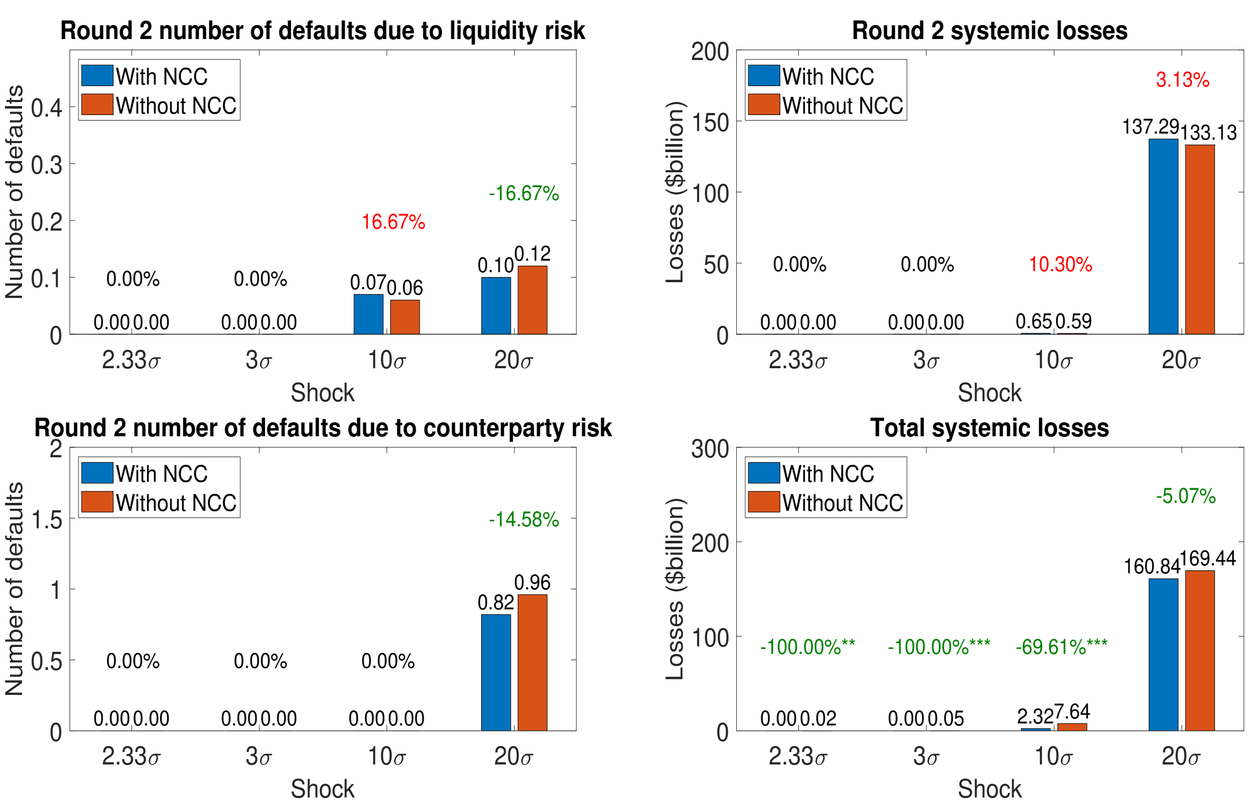

Figure 2.6: Alternative central clearing configurations results - Increased central clearing (second day)

Table 2.4: Alternative central clearing configurations results

This table reports results assuming that the CCP clears 50% and 95% of all derivatives transactions in the Reduced central clearing and Increased central clearing configurations respectively. The banks default due to liquidity risk if their LCR drops to less than 100% and due to counterparty risk if their CAR drops to less than 8%. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

		Reduced central clearing			Increased central clearing		
	Shock	With NCC	Without NCC	% Change	With NCC	Without NCC	% Change
Panel A: Day 1 results							
Defaults due to liquidity risk	$2.33\sigma_0$	1.29	0.03	4200.00***	0.22	0.13	69.23*
	$3\sigma_0$	1.65	0.10	1550.00***	0.37	0.21	76.19**
	$10\sigma_0$	9.39	4.29	118.88***	2.00	1.81	10.50
	$20\sigma_0$	17.91	11.28	58.78***	6.20	5.83	6.35*
Systemic losses ($ billion)	$2.33\sigma_0$	0.00	0.00	0.00	0.00	0.02	−100.00**
	$3\sigma_0$	0.00	1.28	−100.00**	0.00	0.05	−100.00***
	$10\sigma_0$	62.53	156.60	−60.07***	1.67	7.05	−76.33***
	$20\sigma_0$	528.76	664.06	−20.38***	23.55	36.30	−35.13***
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.34	−100.00***	0.00	0.00	0.00
	$20\sigma_0$	1.44	2.89	−50.17***	0.00	0.00	0.00
CCP uncol. losses ($ billion)	$2.33\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$10\sigma_0$	34.88	22.67	53.86***	24.47	23.16	5.69
	$20\sigma_0$	166.70	147.16	13.28***	201.30	193.62	3.97
Panel B: Day 2 results							
Defaults due to liquidity risk	$2.33\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$10\sigma_0$	0.21	0.03	600.00***	0.07	0.06	16.67
	$20\sigma_0$	0.64	0.42	52.38***	0.10	0.12	−16.67
Systemic losses ($ billion)	$2.33\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$10\sigma_0$	9.85	2.43	305.50***	0.65	0.59	10.30
	$20\sigma_0$	41.69	43.76	−4.73	137.29	133.13	3.13
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.04	−100.00**	0.00	0.00	0.00
	$20\sigma_0$	0.24	0.37	−35.14	0.82	0.96	−14.58
Panel C: Days 1&2 results							
Systemic losses ($ billion)	$2.33\sigma_0$	0.00	0.00	0.00	0.00	0.02	−100.00**
	$3\sigma_0$	0.00	1.28	−100.00**	0.00	0.05	−100.00***
	$10\sigma_0$	72.39	159.03	−54.48***	2.32	7.64	−69.61***
	$20\sigma_0$	570.45	707.82	−19.41***	160.84	169.44	−5.07

The CCP's expansion leads to substantially higher systemic losses on day 2 in the most extreme market scenario, from \$41.69 billion or 1.56% of remaining capital under NCC and \$43.76 billion or 1.73% of remaining capital without NCC with reduced central clearing, to \$137.29 billion or 4.33% of remaining capital under NCC and \$133.13 billion or 4.22% of remaining capital without NCC with increased central clearing, an increase of 3.3 times and 3 times respectively. Hence, once the CCP exhausts its pre-funded resources it becomes a source of contagion and the losses it distributes are amplified with its increased presence in the market.

The defaults due to counterparty risk increase with the expansion of central clearing because the CCP distributes larger uncollateralised losses to the surviving CMs via VMGH. However, these defaults remain low as banks are well-capitalised, at 0.24 and 0.37 with and without NCC respectively when the CCP clears 50% of all transactions, to 0.82 and 0.96 when the CCP clears 95% of all transactions.

Finally, the total systemic losses for days 1 and 2 decrease with the expansion of central clearing under all market scenarios due to the beneficial effect of multilateral netting in reducing exposures. In the most extreme market scenario, the losses decrease by 71.80% with NCC as central clearing expands, from \$570.45 billion or 17.86% of total equity with reduced central clearing to \$160.84 billion or 5.04% of total equity with increased central clearing. Without NCC, total systemic losses decrease by 76.06% from \$707.82 billion or 22.16% of total equity with reduced central clearing to \$169.44 billion or 5.31% of total equity with increased central clearing.

The results indicate that the expansion of central clearing is beneficial for financial stability as it substantially reduces total systemic losses, driven by the reduction of first-round losses originating from market shocks due to increasing netting benefits. However, this reduction is accompanied by an increase of second-round losses due to the feedback effect, such that the CCP can distribute losses that are much higher than those due to the market shock when it is dominant in the market. Hence, even though the net reduction is positive (decrease of first-round losses more than offsets increase of second-round ones), the fact that the CCP has the potential to become the main source of stress in the system requires a careful appraisal of its pre-funded resources in the new regulatory environment to ensure it does not contribute to financial instability.

Examining the effect of NCC as the CCP expands, we observe that its effects (both positive and negative) become subdued when it affects only 5% of market activity. In terms of total systemic losses, we observe that the only insignificant difference in means occurs in the increased central clearing configuration under extreme stress. In general, NCC is most effective at reducing systemic losses when central clearing is limited as observed by the reduction of losses between the two configurations for various levels of central clearing. This is intuitive given that bilateral transactions capture a larger fraction of market activity when central clearing is limited.

2.6 Sensitivity analysis

2.6.1 Increased CCP resources

In this subsection we discuss the model results when the CCP increases its pre-funded resources, the IM and the DF, by 100% compared to the baseline configuration. Such an increase would better protect the CCP, reducing the losses it distributes in the second round, at the cost of higher liquidity encumberment of CMs and higher losses in the first round. We can thus use the model to assess which effect dominates and what is the net effect on overall systemic risk.[21] The results are reported in Table A.2 and in Figures A.1 and A.2 in Appendix A.2.

On day 1, the number of defaults due to liquidity risk is slightly higher compared to the baseline configuration under all market conditions due to the higher liquidity encumberment, reaching 12.87 and 9.79 with and without NCC respectively during extreme stress compared to 11.53 and 8.48 in the baseline configuration. The resulting systemic losses also increase, reaching \$205.86 billion or 6.45% of total equity under NCC compared to \$189.59 billion or 5.94% of total equity in the baseline configuration, and \$273.46 billion or 8.56% of total equity without NCC compared to \$254.59 billion or 7.97% of total equity in the baseline configuration. The number of defaults due to counterparty risk increases marginally due to the increased systemic losses, reaching 0.17 under NCC and 0.80 without, compared

[21] This analysis is partial in the sense that it does not capture the change in CMs' incentive to centrally clear if CCP margin costs double. As such, systemic risk could increase if they migrate transactions outside of CCPs.

to 0.13 and 0.67 respectively in the baseline configuration. The CCP suffers uncollateralised losses only in the most extreme market scenario due to its increased resources, reaching \$141.36 billion under NCC and \$127.24 billion without, significantly reduced compared to the baseline configuration losses of \$221.12 billion and \$194.79 billion respectively.

On day 2, the number of defaults due to liquidity risk increases slightly, up to 0.74 under NCC and 0.55 without in the most extreme market scenario, compared to 0.36 and 0.33 with and without NCC respectively in the baseline configuration. This is because the CCP has a larger DF so it asks for more resources to replenish it from the CMs. The systemic losses are greatly reduced, at \$54.96 billion or 1.84% of remaining equity under NCC compared to \$125.58 billion or 4.18% of remaining equity in the baseline configuration, and \$44.29 billion or 1.52% of remaining equity without NCC compared to \$105.02 billion or 3.57% of remaining equity in the baseline configuration. As a result, the defaults due to counterparty risk also decrease, at 0.65 under NCC and 0.80 without compared to 1.65 and 1.48 respectively in the baseline configuration.

Finally, the total systemic losses decrease under severe stress conditions, reaching \$260.82 billion or 8.17% of total equity under NCC compared to \$315.16 billion or 9.87% of total equity in the baseline configuration, and \$317.74 billion or 9.95% of total equity without NCC compared to \$359.61 billion or 11.26% of total equity in the baseline configuration. In other words, a more robust CCP decreases overall systemic risk because the increase in first-round losses due to the higher liquidity risk of CMs is more than offset by the decrease in second-round losses allocated by the CCP due to its larger resources.

2.6.2 Alternative LCR threshold

In this subsection we discuss the model results assuming that the banks default due to liquidity risk if their LCR drops below 70% instead of 100% as in the baseline configuration. In general, the reported effects are reduced if the banks have more available liquidity to pay their VM obligations, although the actual resources that they can utilise for their derivatives activities are likely to be only a fraction of their total HQLA. The results are reported in Table A.3 and in Figures A.3 and A.4 in Appendix A.2.

The number of defaults due to liquidity risk on day 1 is substantially reduced since banks have more HQLA available, reaching 2.98 in extreme stress under NCC and 1.92 without, higher under NCC by 55.21%, compared to 11.53 and 8.48 respectively in the baseline configuration, higher under NCC by 35.97%. This leads to systemic losses of up to $52.34 billion under NCC and $65.83 billion without, or 1.64% and 2.06% of total equity respectively, reduced by 20.50% under NCC. These compare to the baseline results of $189.59 billion or 5.94% of the total equity under NCC and $254.59 billion or 7.97% of total equity without, reduced by 25.53% under NCC. As a result, the number of defaults due to counterparty risk is also lower, reaching 0.03 under NCC and 0.19 without in extreme stress, decreased by 84.21% under NCC, compared to 0.13 and 0.67 respectively in the baseline configuration, decreased by 80.60% under NCC. The CCP's uncollateralised losses reach $58.55 billion under NCC and $50.25 billion without, increased by 16.52% with the introduction of NCC, compared to $221.12 billion and $194.79 billion respectively in the baseline configuration, increased by 13.52% with NCC. Hence, even though the magnitude of day 1 defaults and losses decreases when we lower the minimum LCR bound, the relative difference between the two configurations with and without NCC remains similar, which provides support to our baseline results regarding the effects of NCC.

On day 2, the number of defaults due to liquidity risk again decreases, reaching only 0.01 under extreme stress with and without NCC compared to 0.36 and 0.33 in the baseline configuration. The systemic losses are also lower, at $23.53 billion under NCC or 0.75% of remaining equity, and $16.61 billion without or 0.53% of remaining equity, higher under NCC by 41.64%. These compare to the baseline results of $125.58 billion under NCC or 4.18% of remaining total equity and $105.02 billion without or 3.57% of remaining equity, increased by 19.58% under NCC. The resulting defaults due to counterparty risk reach 0.09 under NCC and 0.19 without, compared to 1.65 and 1.48 in the baseline configuration.

Finally, the total systemic losses reach $75.87 billion or 2.38% of total equity under NCC and $82.44 billion or 2.58% of total equity without, decreased by $6.6 billion or 7.98% under NCC. This decrease is not statistically significant, in contrast to the decrease of 12.36% in total systemic losses in the baseline configuration from $359.61 billion without NCC to $315.16 billion following its introduction. This is because the decrease of day 1 losses of $13.49 billion is more comparable to the increase of day 2 losses of $6.92 billion, compared to the baseline configuration decrease of day 1 losses of $65 billion and increase of day 2 losses of $20.56 billion. In other words, when the banks utilise more resources to pay their VM obligations the beneficial effect of NCC at reducing first-round losses is almost entirely offset by the increase of second-round losses due to the CCP's operations, so the net effect on total systemic losses is less pronounced. This result further highlights the importance of containing the potential of the CCP to act as a source of contagion during extreme stress, as it can potentially negate the reduction of systemic losses originating from the market shock with the introduction of NCC.

2.6.3 Static market participants

In this subsection we discuss results from a static variant of the model. Under this configuration the CMs are not allowed to rebalance their portfolios following the shock on the first day but they passively accept the resulting losses as they crystallise. This mimics the methodology of Heath et al. (2016) and serves as a useful benchmark in order to compare with our baseline configuration's results. We report the results in Table A.4 and in Figures A.5 and A.6 in Appendix A.2.

Overall, we observe that the number of defaults on day 1 tends to be higher for mild shocks but slightly lower for severe shocks under the static configuration compared to the baseline one. This is because in the presence of small shocks and few distressed market participants, healthy CMs are able to accommodate the needs of the former so they are able to avoid default. However, once extreme shocks occur everyone runs for the exit due to large VM obligations and the system becomes more fragile (Pedersen, 2009).

In the most extreme market scenario, the first-round losses in the static setup are $198.15 billion or 6.20% of total equity under NCC and $249.63 billion or 7.82% of total equity without, compared to $189.59 billion or 5.94% of total equity and $254.59 billion or 7.97% of total equity respectively in the baseline configuration. While the number of defaults due to liquidity risk is higher in the baseline configuration, the systemic losses are comparable. This is because in the baseline configuration there is a higher number of defaults of small (periphery) banks and lower number of defaults of core (large) banks. Intuitively, larger banks would be more resilient to liquidity shocks than smaller ones and be able to more quickly adapt to changing market conditions.

Due to the similar systemic losses, the number of defaults due to counterparty risk remains virtually the same, at 0.13 and 0.66 with and without NCC respectively, compared to 0.13 and 0.67 in the baseline configuration. The CCP also sustains similar losses, \$220.49 billion with NCC and \$192.94 billion without compared to \$221.12 billion and \$194.79 billion in the baseline configuration respectively, leading to similar second-round losses. These are capped at \$120.98 billion or 4.04% of remaining equity under NCC and \$104.31 billion or 3.54% of remaining equity without, compared to \$125.58 billion or 4.18% of remaining equity and \$105.02 billion or 3.57% of remaining equity respectively in the baseline configuration.

Finally, the total systemic losses in the most extreme market scenario under the static setup are \$319.13 billion or 9.99% of total equity under NCC and \$353.94 billion or 11.08% of total equity without, compared to \$315.16 billion or 9.87% of total equity and \$359.61 billion or 11.26% of total equity respectively under the baseline configuration. While the results in terms of total systemic risk are similar between the baseline and static configurations, which provides robustness to our main findings, the change in the composition of defaulting banks highlights the fragility of the system during times of stress.

2.6.4 CCP interoperability

In the final subsection we discuss results from an alternative model configuration which showcases how our framework can be used to assess a variety of different policies. In particular, we consider the case of two competing CCPs which may or may not be linked to each other through interoperability arrangements. Such arrangements allow for a buyer and a seller to clear their trade through different CCPs, which makes the CCPs clearing members of each other.

The main benefit arising from interoperability is the reduction of exposures in a fragmented clearing market since positions can be netted across CCPs, thus lowering the margin costs of market participants. On the other hand, interoperability arrangements can potentially increase systemic risk because they create exposures between CCPs so a CM default in one CCP can lead to spillover losses to CMs of the other CCP. Furthermore, CCPs do not have control over the amount of exposure that can build up between them as it depends on the CMs' trades.

To date, CCP interoperability has been mainly applied in vanilla securities rather than derivatives CCPs due to the inherently higher complexity of managing risks of derivatives contracts with long maturities, which has hampered its widespread adoption (McPartland and Lewis, 2016). Theoretical research has found that CCP interoperability can lead to significant reduction of exposures in fragmented clearing markets, but at the same time it can also increase systemic risk due to undercollateralisation of cross-CCP exposures (Mägerle and Nellen, 2015). In our paper, we attempt to quantify the trade-off between decreased exposures and increased CCPs' propensity for contagion. While our results are stylised and do not take into account all the complexities that would arise from derivatives CCP interoperability arrangements, we contribute by providing empirical estimates of the trade-off to assess which effect dominates.

As mentioned before, we consider two competing CCPs. In the case where there are no interoperability arrangements, we assume that the first CCP manages the majority of the trades of the Core-16 banks, while the second CCP caters for the trades of the Periphery-23 banks between themselves and with the Core-16 banks. In other words, with no interoperability the Core-16 banks are CMs of both CCPs, while the Periphery-23 banks are CMs of the second CCP only. As a result, in this configuration collateral requirements are not efficient since the Core-16 banks' exposures are fragmented across two CCPs, leading to higher IM requirements. Specifically, the first CCP collects \$156.2 billion in IM while the second CCP collects \$123.2 billion, so the total IM collected is \$279.4 billion. This is 25% higher than the IM posted in the baseline configuration of \$224.3 billion, a significant increase.

When interoperability arrangements exist, the Core-16 banks do not need to be CMs of the second CCP in order to accommodate the Periphery-23 banks' trades. Hence, in this case the Core-16 banks are CMs of the first CCP only while the Periphery-23 banks are CMs of the second CCP as before. However, the CCPs now have an exposure between themselves equal to the value of the trades between the Core-16 and Periphery-23 banks. This configuration lowers the IM requirements to the same level as in the baseline configuration because of the netting benefits, with the first CCP collecting \$172.9 billion in IM and the second one collecting \$51.4 billion for a total of \$224.3 billion.

Apart from these changes the model works as before, although in the case of interoperability if a CM of one CCP indirectly connected to the CM of the other defaults and creates losses for the CCP that are not covered by its pre-funded resources, these losses can be transmitted to the other CCP and mutualised across its CMs. We assume that non-central clearing is present in both configurations in order to focus on the effects of interoperability and not confound our results. The results are presented in Table A.5 and in Figures A.7 - A.9 in Appendix A.2.

On day 1, defaults due to liquidity risk remain significantly lower under interoperability compared to without in all cases, reaching 11.63 and 13.17 on average respectively in the most extreme market scenario. This is because as explained before the presence of interoperability lowers the system-wide IM requirements and hence the CMs' liquidity encumberment. This translates into lower day 1 systemic losses, reaching $189.78 billion or 5.94% of initial equity under interoperability and $220.51 billion or 6.90% of initial equity without, reduced by 13.93%. The resulting defaults due to counterparty risk are thus also lower under interoperability compared to without, at 0.11 and 0.16 respectively, although there is no statistical difference between them.

The first CCP suffers slightly lower uncollateralised losses under interoperability compared to without as a result of the lower number of defaults due to liquidity risk, reaching $183.98 billion and $185.88 billion respectively under extreme market stress, statistically the same. However, the second CCP's losses under interoperability are significantly lower compared to without, reaching $31.37 billion and $93.01 billion respectively, a reduction of 66.28%. This is because without interoperability it includes all 39 banks as CMs while with interoperability only the Periphery-23 banks are its CMs. As a result, its exposures are greatly reduced under interoperability as the Core-16 banks do not need to act as its CMs to accommodate the Periphery-23 banks' trades, leading to lower losses in times of stress.

On day 2, defaults due to liquidity risk are slightly higher under interoperability compared to without, at 0.43 and 0.28 respectively. The systemic losses reach $101.59 billion or 3.38% of remaining equity under interoperability and $122.99 billion or 4.14% of remaining equity without, reduced by 17.40%. This is because even though under interoperability there is transmission of losses across CCPs, they only reach $250 million after taking into account the collateral which are more than offset by the significant reduction of the second CCP's uncollateralised losses and their subsequent mutualisation across its CMs. As a result, the number of defaults due to counterparty risk due to VMGH decreases by 24.41% with the introduction of interoperability from 1.68 to 1.27. Finally, the total systemic losses always remain lower under interoperability compared to without, reaching $291.37 billion or 9.12% of total equity and $343.49 billion or 10.75% of total equity respectively, reduced by 15.17%.

Our results indicate that interoperability arrangements can in fact reduce liquidity, counterparty and systemic risks. As long as their introduction leads to smaller CCPs in terms of membership base, the resulting reduction in CCP uncollateralised losses more than offsets cross-CCP losses that can occur even under extreme market conditions, while the netting benefits result in lower CM liquidity encumberment and further reduction of CCP losses. To the best of our knowledge, this is a novel finding in the small literature on CCP interoperability arrangements. While it is not intended to guide policy due to the stylised nature of the model, it indicates that further research should be conducted to assess how interoperability can affect systemic risk.

2.7 Conclusion

In this paper we develop a network model incorporating the largest dealer banks in the OTC derivatives markets as well a fictitious CCP that is the dominant counterparty. We consider two system configurations, one in which the banks post collateral between themselves in bilateral transactions and one in which they don't in order to assess the effects of non-central clearing on counterparty, liquidity and systemic risks.

We report the effectiveness of non-central clearing at reducing counterparty and systemic risks under mild and severe market conditions. Even though a higher number of market participants default on their obligations due to liquidity risk under extreme stress following the introduction of non-central clearing, the collateral posted in bilateral trades results in lower systemic losses and protects market participants from counterparty risk.

However, the implications for the relationship between central and non-central clearing are less clear-cut. A higher number of defaulting banks due to increased liquidity risk leads to higher losses for the CCP which in turn transmits them back to the surviving market participants. This effect is reduced as the CCP becomes more dominant in the market but the knock-on losses originating from the CCP may surpass those due to the initial market shock as a result. Hence, our analysis suggests that the proliferation of derivatives clearing necessitates the adoption of a holistic view by the regulatory authorities on how different market participants, including banks and CCPs, can propagate shocks during times of stress.

To conclude, our paper provides a quantitative assessment of the potential sources of stress in the cleared OTC derivatives markets. We highlight the importance of liquidity risk during times of stress and its potential to destabilise the CCP, leading to significant feedback effects. We have used the framework to empirically assess various recommendations regarding the optimal CCP design that will maximise the welfare of itself and its members such as interoperability arrangements. Future work can expand the framework to provide further insights.

Appendix A

A.1 CCP auction optimal bidding function

In this section we derive the optimal bidding function of our auction setup which coincides with the one from the independent private value model.

Consider M risk-neutral bidders (the participating CMs), each assigning a private and independent value u_i on the auction item, in this case the defaulting CMs' portfolio. Each bidder knows its valuation and the fact that the opponents' valuations are drawn independently from the same distribution F with density f and support $[\underline{u}, \overline{u}]$. Note that it may be that $\underline{u} < 0$ and $\overline{u} > 0$ since the CMs may assign both positive and negative values to the portfolio depending on their existing positions as explained in the main text.

Let the payoff of each bidder be:

$$\pi_i = \begin{cases} u_i - b_i - q_i \text{ if } b_i > \max_{j \neq i} b_j \\ -q_i \text{ otherwise} \end{cases} \tag{A.1.1}$$

where u_i is the private valuation, b_i is the bid and q_i is a loss function that depends on the bidder's DF contribution, the uncollateralised losses faced by the CCP and the resources used by the CCP prior to the bidder's Powers of Assessment contribution which include the defaulted CMs' IM, the entire DF, the skin-in-the-game equity and any other bidders' Powers of Assessment contributions used according to the bidding behavior. Except for its own DF contribution, the equity contribution of the CCP and the total DF amount, all other quantities are unknown to the bidder.

The total VM owed to the CCP by defaulted CMs belonging in the set H is $\sum_{h \in H} VM^0_{hi}$.

Note that CMs that defaulted due to missed VM receipts violating condition (2.15) have successfully repaid their VM obligations since they satisfy condition (2.14) hence they do not owe VM to the CCP. As such we only consider here the subset H that includes the CMs that violated (2.14) and not D that also includes those that failed condition (2.15). The function is of the form:

$$q_i = \min\left\{2F_i, \max\left\{0, \sum_{h\in H} VM^0_{hi} - \left(\sum_{h\in H} IM^0_{hi} + T + DF + \sum_{k\in K} 2F_k\right)\right\}\right\} \text{ for } j = n+1 \tag{A.1.2}$$

where T is the equity tranche used by the CCP and K is the set of bidders having posted lower bids than bidder i and have responded to the Powers of Assessment in full by contributing twice their original DF amounts F_k. The number of bidders belonging in this set increases as the bid posted by bidder i increases in ranks. Hence, if the losses are sufficiently covered by the Powers of Assessment the function decreases to zero as the ranking of the bid increases. However, the only known variables to CM i are F_i, T and DF.

Since the function is capped at $2F_i$, the worst-case scenario is the one where the expected payoff is minimised, i.e. the one where the loss function is maximised in every state of nature irrespectively of the bidding order. Formally, each bidder chooses a value $x_i \in [\underline{u}, \overline{u}]$ to assign to the bid $b_i = b(x_i)$ to maximise the expected payoff $\pi_i = \pi(x_i)$ given the least favorable state of nature according to the maximin operator:

$$\max_{x_i} \min_{q_i\in Q} \left\{[u_i - b_i - q_i]\mathrm{P}\left[b_i > \max_{j\neq i} b_j\right] - \sum_{m=3}^{M} q_i \mathrm{P}\left[b_i > \{b\}\right] - q_i \mathrm{P}\left[b_i < \min_{j\neq i} b_j\right]\right\} \tag{A.1.3}$$

where $\mathrm{P}[\cdot]$ denotes the probability, Q denotes the set of all possible values of q_i and $\{b\} = \{b_m, \ldots, b_M\}$ denotes the set of ordered bids.

This equals:

$$\max_{x_i} \left\{[u_i - b_i - 2F_i]\mathrm{P}\left[b_i > \max_{j\neq i} b_j\right] - \sum_{m=3}^{M} 2F_i \mathrm{P}\left[b_i > \{b\}\right] - 2F_i \mathrm{P}\left[b_i < \min_{j\neq i} b_j\right]\right\} \tag{A.1.4}$$

or simply:

$$\max_{x_i} \left\{ [u_i - b_i] \mathrm{P}\left[b_i > \max_{j \neq i} b_j \right] - 2F_i \right\} \tag{A.1.5}$$

since the loss $2F_i$ occurs in all states of nature, i.e. with probability 1.

The probability that a bid is the k-th highest among M bids is given by order statistics:

$$\begin{aligned} &\mathrm{P}[b(x_1), ..., > b(x_{k-1}) > b(x_k) > b(x_{k+1}), ..., > b(x_M)] \\ &= \mathrm{P}[x_1, ..., > x_{k-1} > x_k > x_{k+1}, ..., > x_M] \\ &= \binom{M-1}{k-1} (1 - F(x_i))^{k-1} F(x_i)^{M-k} \end{aligned}$$

Note that the second line uses the assumption of b being strictly increasing in x.

Hence the probability of winning $(k = 1)$ is equal to:

$$\mathrm{P}\left[b_i > \max_{j \neq i} b_j \right] = F(x_i)^{M-1} \tag{A.1.6}$$

As such the payoff becomes:

$$\max_{x_i} \left\{ [u_i - b_i] F(x_i)^{M-1} - 2F_i \right\} \tag{A.1.7}$$

First order condition (FOC) yields:

$$\frac{\vartheta \pi(x_i)}{\vartheta x_i} = \pi'(x_i) = 0 \Leftrightarrow (M-1)F(x_i)^{M-2} f(x_i)(u_i - b(x_i)) - b'(x_i)F(x_i)^{M-1} = 0 \tag{A.1.8}$$

As can be seen, the Powers of Assessment contribution $2F_i$ disappears in the FOC. In that case, this is the standard IPV model.

In a symmetric equilibrium the expected profit is maximised at $x_i = u_i$.

We solve for the optimal bid as follows. From (A.1.8):

$$\begin{aligned} b'(u_i)F(u_i)^{M-1} &= (M-1)F(u_i)^{M-2} f(u_i)(u_i - b(u_i)) \\ \Leftrightarrow [b(u_i)F(u_i)^{M-1}]' &= u_i(M-1)F(u_i)^{M-2} f(u_i) \end{aligned} \tag{A.1.9}$$

This is an ordinary differential equation which can be solved by integration:

$$\int_{\underline{u}}^{u_i} d[b(x_i)F(x_i)^{M-1}]' = \int_{\underline{u}}^{u_i} x_i(M-1)F(x_i)^{M-2}f(x_i)dx_i$$
$$\Leftrightarrow b(u_i)F(u_i)^{M-1} - b(\underline{u})F(\underline{u})^{M-1} = \int_{\underline{u}}^{u_i} x_i(M-1)F(x_i)^{M-2}f(x_i)dx_i$$

Since $F(\underline{u}) \to 0$ solving for $b(u_i)$ yields the optimal equilibrium bid:

$$b(u_i) = \begin{cases} \frac{(M-1)\int_{\underline{u}}^{u_i} x_i F(x_i)^{M-2} f(x_i)dx_i}{F(u_i)^{M-1}} \text{ if } \underline{u} < u_i \leq \overline{u} \\ -\infty \text{ if } u_i = \underline{u} \end{cases} \tag{A.1.10}$$

i.e. equation (2.22).

To verify that $x_i = u_i$ is indeed an equilibrium it suffices to show from (A.1.8) that:

$$\begin{aligned} &(M-1)F(x_i)^{M-2}f(x_i)(u_i - b(x_i)) - b'(x_i)F(x_i)^{M-1} = 0 \\ &\Leftrightarrow (M-1)F(x_i)^{M-2}f(x_i)(u_i - x_i) = 0 \end{aligned} \tag{A.1.11}$$

Hence from (A.1.11) if $x_i < u_i$ then $\pi'(x_i) > 0$ and if $x_i > u_i$ then $\pi'(x_i) < 0$ so $x_i = u_i$ maximises the expected payoff and the optimal solution is an equilibrium.

A.2 Additional Tables and Figures

Table A.1: List of banks

Core-16	Periphery-23
Bank of America Merrill Lynch	ANZ Banking Group
Barclays	Banca IMI SpA
BNP Paribas	Banco Santander
Citigroup	Bank of China
Crédit Agricole	Bank of New York Mellon
Credit Suisse	BBVA
Deutsche Bank	Commerzbank
Goldman Sachs	Commonwealth Bank
HSBC	Danske Bank
JP Morgan Chase	Dexia
Morgan Stanley	DZ Bank
Nomura Group	Intesa
Royal Bank of Scotland	LBBW
Société Générale	Lloyds Banking Group
UBS	MUFG
Wells Fargo	Mizuho
	National Australia Bank
	Nordea Bank
	Rabobank
	Standard Chartered
	State Street
	UniCredit Group
	Westpac

Source: MAGD (2013)

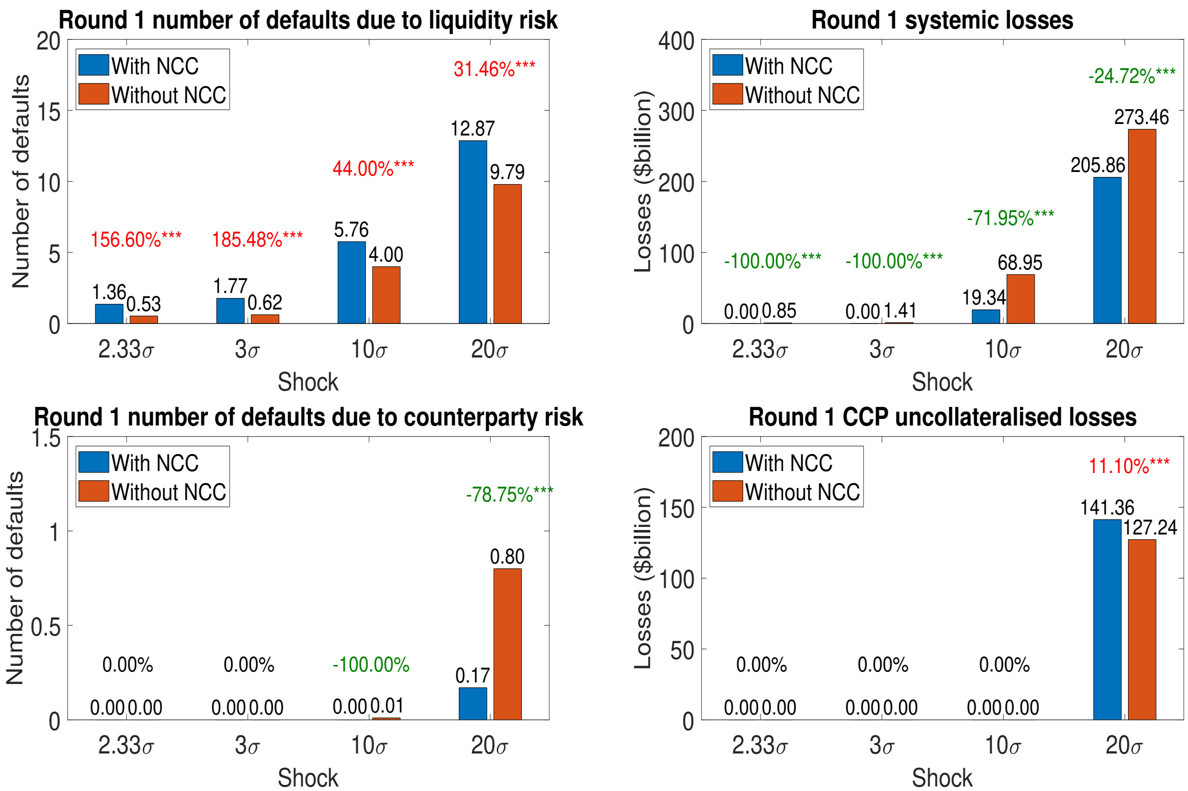

Figure A.1: Increased CCP resources configuration results (first day)

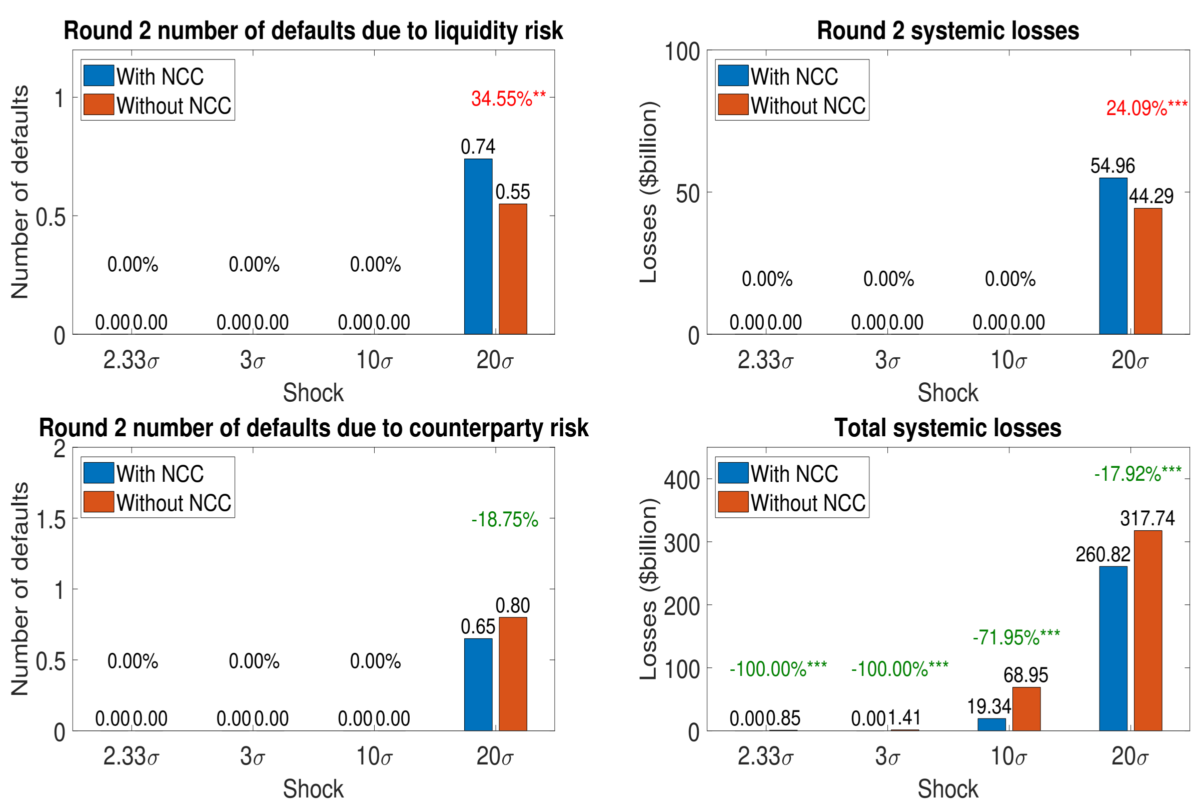

Figure A.2: Increased CCP resources configuration results (second day)

Table A.2: Increased CCP resources configuration results

This table reports results assuming that the CCP has double the resources it collects in the baseline configuration. The CCP is assumed to clear 75% of all derivatives transactions, and the banks default due to liquidity risk if their LCR drops to less than 100% and due to counterparty risk if their CAR drops to less than 8%. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	Shock	With NCC	Without NCC	% Change
Panel A: Day 1 results				
Defaults due to liquidity risk	$2.33\sigma_0$	1.36	0.53	156.60***
	$3\sigma_0$	1.77	0.62	185.48***
	$10\sigma_0$	5.76	4.00	44.00***
	$20\sigma_0$	12.87	9.79	31.46***
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.85	−100.00***
	$3\sigma_0$	0.00	1.41	−100.00***
	$10\sigma_0$	19.34	68.95	−71.95***
	$20\sigma_0$	205.86	273.46	−24.72***
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.01	−100.00
	$20\sigma_0$	0.17	0.80	−78.75***
CCP uncollateralised losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	141.36	127.24	11.10***
Panel B: Day 2 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	0.74	0.55	34.55**
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	54.96	44.29	24.09***
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	0.65	0.80	−18.75
Panel C: Days 1&2 results				
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.85	−100.00***
	$3\sigma_0$	0.00	1.41	−100.00***
	$10\sigma_0$	19.34	68.95	−71.95***
	$20\sigma_0$	260.82	317.74	−17.92***

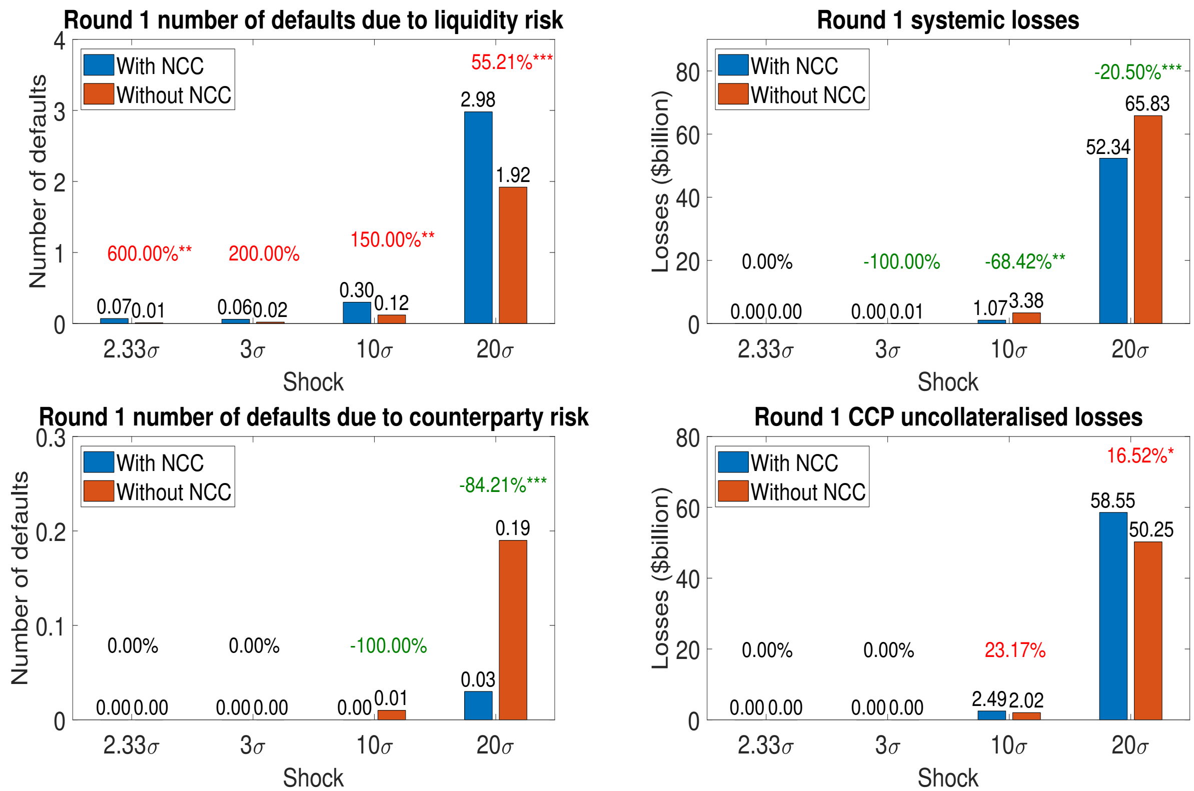

Figure A.3: Alternative LCR threshold configuration results (first day)

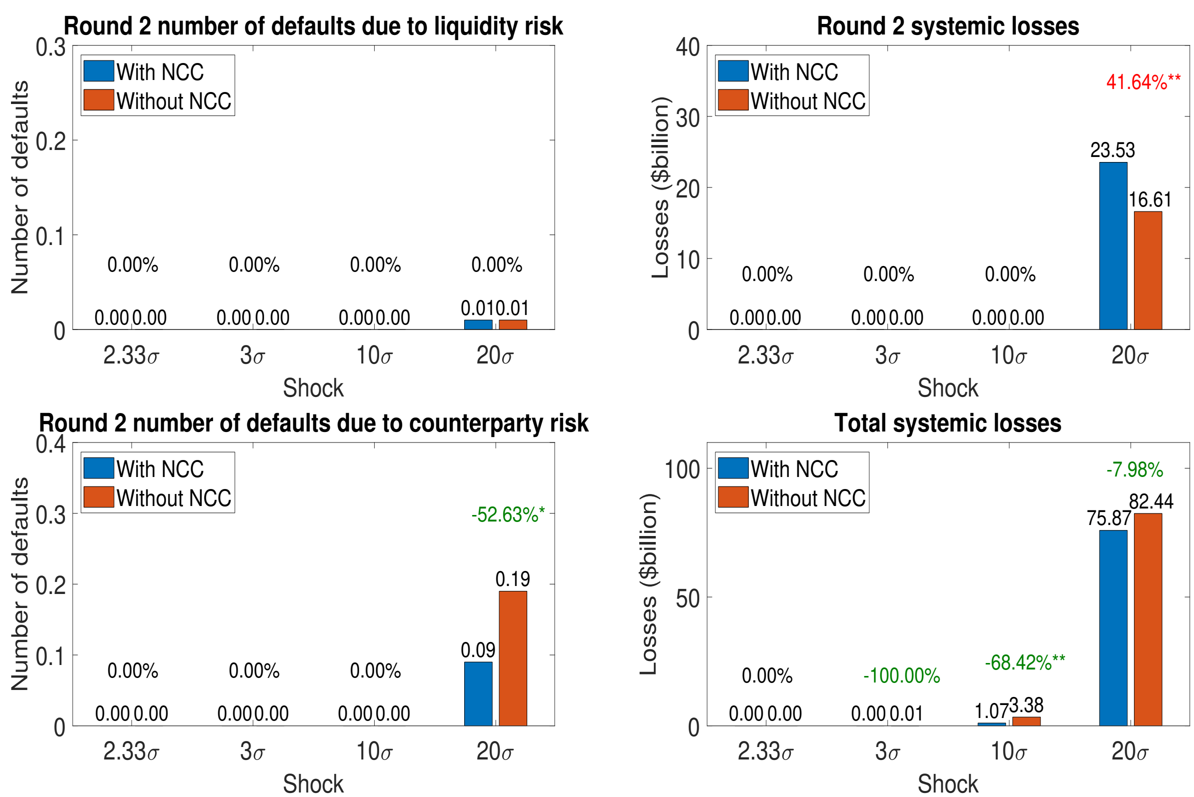

Figure A.4: Alternative LCR threshold configuration results (second day)

Table A.3: Alternative LCR threshold configuration results

This table reports results assuming a lower LCR threshold. The CCP is assumed to clear 75% of all derivatives transactions, and the banks default due to liquidity risk if their LCR drops to less than 70% and due to counterparty risk if their CAR drops to less than 8%. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	Shock	With NCC	Without NCC	% Change
Panel A: Day 1 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.07	0.01	600.00**
	$3\sigma_0$	0.06	0.02	200.00
	$10\sigma_0$	0.30	0.12	150.00**
	$20\sigma_0$	2.98	1.92	55.21***
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.01	−100.00
	$10\sigma_0$	1.07	3.38	−68.42**
	$20\sigma_0$	52.34	65.83	−20.50***
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.01	−100.00
	$20\sigma_0$	0.03	0.19	−84.21***
CCP uncollateralised losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	2.49	2.02	23.17
	$20\sigma_0$	58.55	50.25	16.52*
Panel B: Day 2 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	0.01	0.01	0.00
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	23.53	16.61	41.64**
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	0.09	0.19	−52.63*
Panel C: Days 1&2 results				
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.01	−100.00
	$10\sigma_0$	1.07	3.38	−68.42**
	$20\sigma_0$	75.87	82.44	−7.98

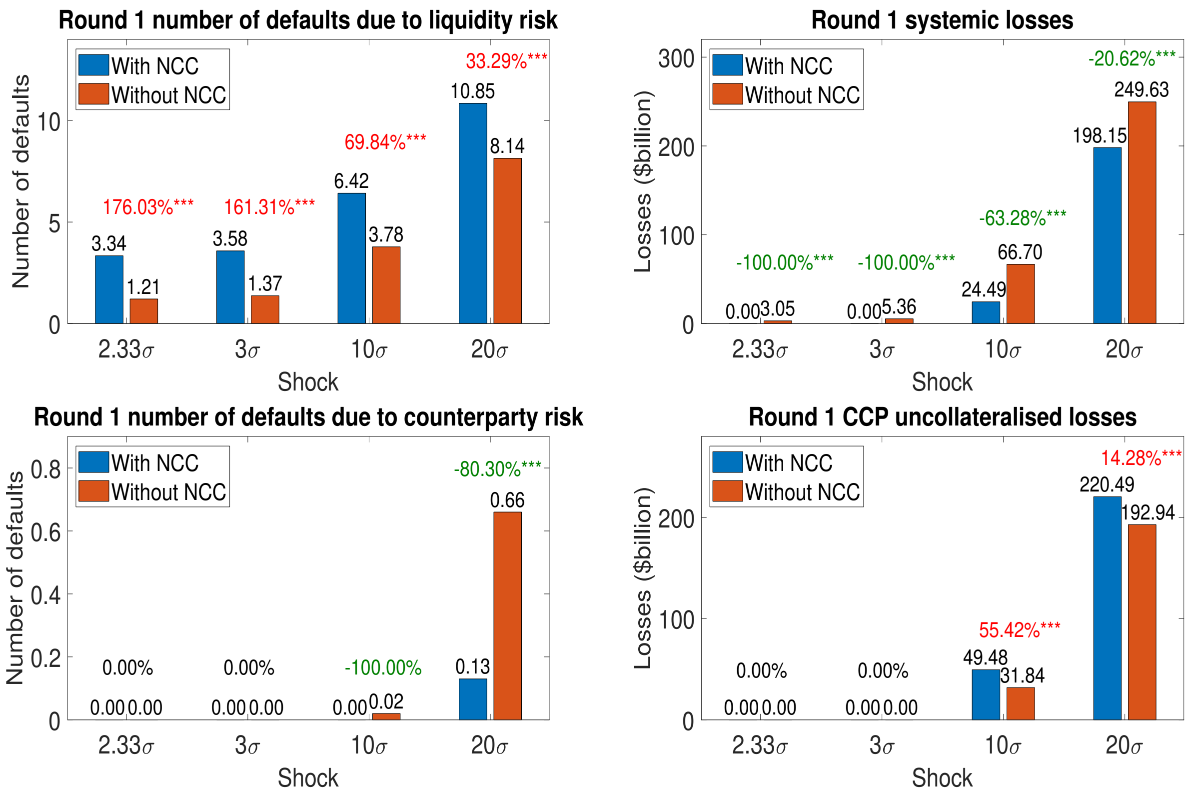

Figure A.5: Static configuration results (first day)

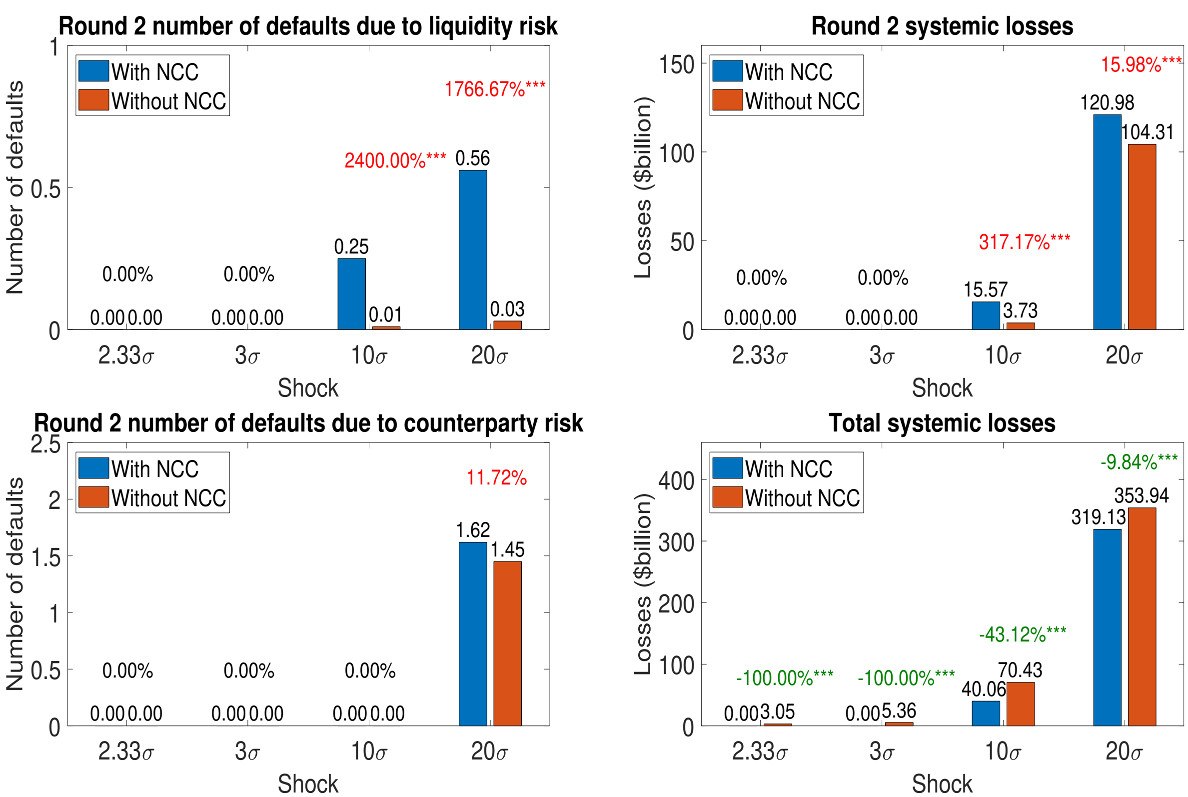

Figure A.6: Static configuration results (second day)

Table A.4: Static configuration results

This table reports results assuming that the banks do not rebalance their portfolios following the market shock. The CCP is assumed to clear 75% of all derivatives transactions, and the banks default due to liquidity risk if their LCR drops to less than 100% and due to counterparty risk if their CAR drops to less than 8%. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	Shock	With NCC	Without NCC	% Change
Panel A: Day 1 results				
Defaults due to liquidity risk	$2.33\sigma_0$	3.34	1.21	176.03***
	$3\sigma_0$	3.58	1.37	161.31***
	$10\sigma_0$	6.42	3.78	69.84***
	$20\sigma_0$	10.85	8.14	33.29***
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	3.05	−100.00***
	$3\sigma_0$	0.00	5.36	−100.00***
	$10\sigma_0$	24.49	66.70	−63.28***
	$20\sigma_0$	198.15	249.63	−20.62***
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.02	−100.00
	$20\sigma_0$	0.13	0.66	−80.30***
CCP uncollateralised losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	49.48	31.84	55.42***
	$20\sigma_0$	220.49	192.94	14.28***
Panel B: Day 2 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.25	0.01	2400.00***
	$20\sigma_0$	0.56	0.03	1766.67***
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	15.57	3.73	317.17***
	$20\sigma_0$	120.98	104.31	15.98***
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	1.62	1.45	11.72
Panel C: Days 1&2 results				
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	3.05	−100.00***
	$3\sigma_0$	0.00	5.36	−100.00***
	$10\sigma_0$	40.06	70.43	−43.12***
	$20\sigma_0$	319.13	353.94	−9.84***

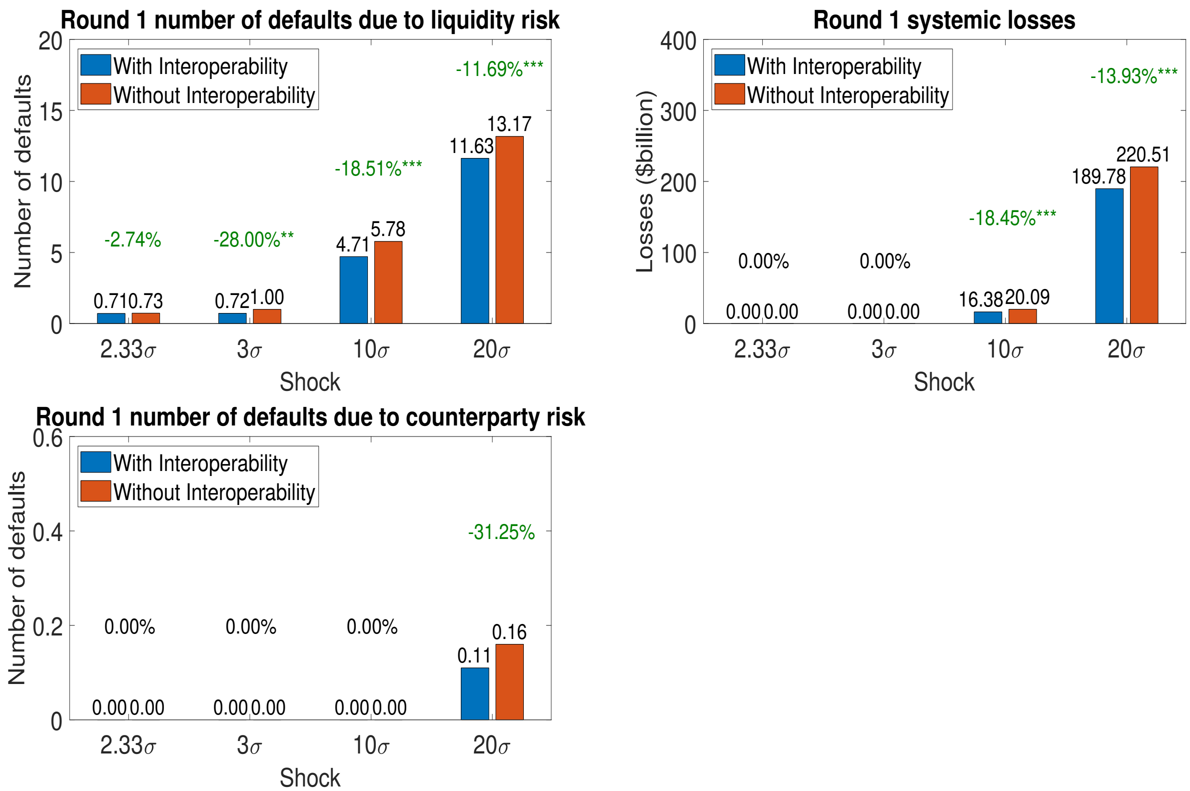

Figure A.7: Interoperability configuration results 1 (first day)

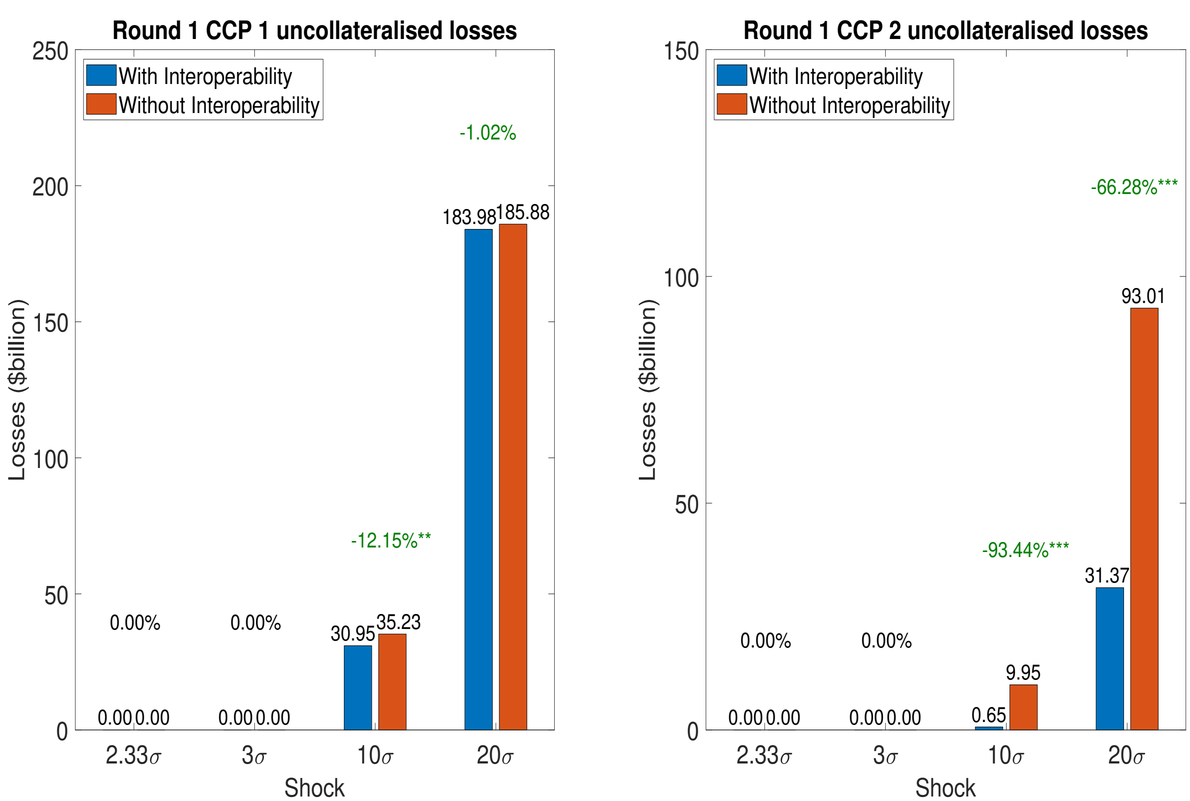

Figure A.8: Interoperability configuration results 2 (first day)

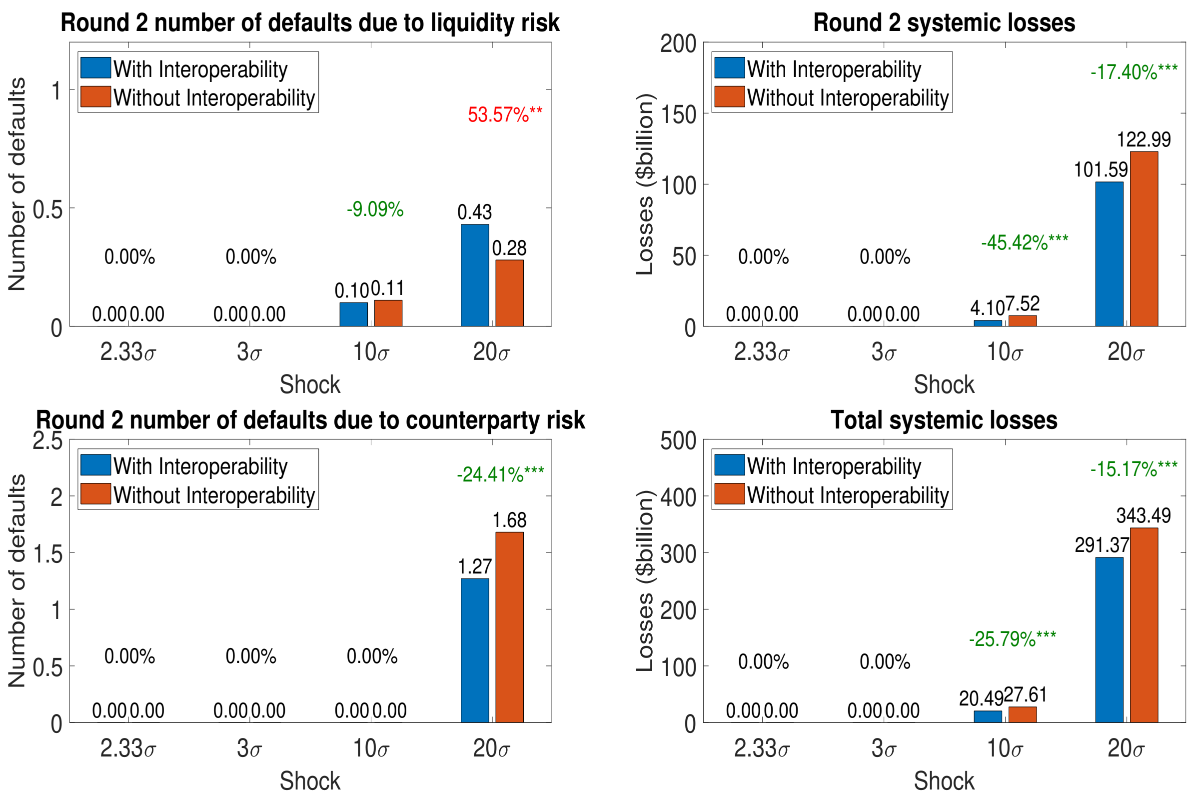

Figure A.9: Interoperability configuration results (second day)

Table A.5: Interoperability configuration results

This table reports results assuming that two CCPs clearing 75% of all derivatives transactions may or may not form interoperability arrangements. The banks default due to liquidity risk if their LCR drops to less than 100% and due to counterparty risk if their CAR drops to less than 8%. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	Shock	With Interop.	Without Interop.	% Change
Panel A: Day 1 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.71	0.73	-2.74
	$3\sigma_0$	0.72	1.00	-28.00^{**}
	$10\sigma_0$	4.71	5.78	-18.51^{***}
	$20\sigma_0$	11.63	13.17	-11.69^{***}
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	16.38	20.09	-18.45^{***}
	$20\sigma_0$	189.78	220.51	-13.93^{***}
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	0.11	0.16	-31.25
CCP 1 uncollateralised losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	30.95	35.23	-12.15^{**}
	$20\sigma_0$	183.98	185.88	-1.02
CCP 2 uncollateralised losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.65	9.95	-93.44^{***}
	$20\sigma_0$	31.37	93.01	-66.28^{***}
Panel B: Day 2 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.10	0.11	-9.09
	$20\sigma_0$	0.43	0.28	53.57^{**}
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	4.10	7.52	-45.42^{***}
	$20\sigma_0$	101.59	122.99	-17.40^{***}
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	1.27	1.68	-24.41^{***}
Panel C: Days 1&2 results				
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	20.49	27.61	-25.79^{***}
	$20\sigma_0$	291.37	343.49	-15.17^{***}

Chapter 3

Information and liquidity linkages in ETFs and underlying markets[1]

Abstract

We find that exchange-traded funds (ETFs) have differential effects on the underlying equities and corporate debt securities. First, ETFs propagate liquidity shocks to equities but not to debt securities. Second, ETF flows affect the underlying equities' returns to a much higher degree than debt securities' returns. Third, higher ETF ownership increases equities' volatility but decreases debt securities' volatility. The results are consistent with the view that the higher accessibility of equities facilitates the formation of strong information links with ETFs and encourages arbitrage activity, which makes equities' prices sensitive to ETF demand shocks and creates the potential for illiquidity contagion when this link is disrupted. In contrast, the hard-to-access nature of corporate debt securities results in weak information links with ETFs and inhibits arbitrage activity which reduces commonalities between the two markets.

[1]This essay is based on the working paper titled "Information and liquidity linkages in ETFs and underlying markets" co-authored with Paweł Fiedor (Central Bank of Ireland), available as a Research Technical Paper of the Central Bank of Ireland. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Central Bank of Ireland.

3.1 Introduction

Turmoil in one market can affect other markets when assets are linked through information channels, creating comovements in liquidity, prices and volatility. Information links between assets exist when investors use information from one asset to infer the price of another. However, these links can trigger contagion effects when investors mistakenly believe that idiosyncratic shocks in one asset reveal information about the other asset, increasing volatility (King and Wadhwani, 1990), or when a liquidity dry-up in one asset makes investors unable to reliably price the other, propagating liquidity shocks (Cespa and Foucault, 2014).

In this paper, we provide novel evidence for this transmission mechanism by looking at the Irish exchange-traded funds (ETFs) and their underlying equities and corporate debt securities using a proprietary dataset from the Central Bank of Ireland. ETF shares can be traded intradaily on an exchange, which attracts high-frequency trading. In addition, ETF shares and the underlying securities are subject to arbitrage activity that exploits price differences, which creates a link between the two markets. Finally, ETFs as index products emphasize the systematic factor of the underlying assets, so they can become the key mover of the index as well as the underlying assets if they dominate the markets (Bhattacharya and O'Hara (2020), Glosten et al. (2020)). As a result, ETFs provide a natural testing ground to assess the effects of information links between markets.

We investigate the effects of ETFs on the underlying equities' and corporate debt securities' liquidity, returns and volatility. By looking at both equities and debt securities, we are able to assess how the ETF effects differ according to the unique characteristics of each market. Specifically, we argue that the strength of the information link and the resulting degree of liquidity, returns and volatility comovement depends on the accessibility of the underlying markets, i.e. the ease with which investors can trade in them. This is because a higher accessibility facilitates the incorporation of information from the linked asset, and incentivises market participants to actively trade the underlying assets in order to exploit arbitrage opportunities with ETF shares which increases the transmission of shocks between markets.

We expect ETFs to form stronger information links with the underlying exchange-traded equities than with the underlying over-the-counter-traded (OTC) corporate debt securities due to the lower accessibility of the latter arising from the significant search and transaction costs of OTC markets (Vayanos and Wang, 2007). The difference in accessibility between equities and corporate debt securities has been further amplified by the post-crisis banking regulations which have caused a deterioration of corporate debt markets' liquidity due to the dealers' contraction of market-making activities (Bessembinder et al. (2018), Bao et al. (2018)), while equity markets' liquidity has recovered from the crisis period (Anand et al., 2013). Even though there certainly exist individual equities that are less liquid than corporate debt securities, the findings of these papers suggest that there is a significant overall divergence in the liquidity of these two markets which affects their accessibility.

While the literature on ETFs and underlying equities has found strong effects on price and liquidity comovements due to arbitrage (Da and Shive (2015), Agarwal et al. (2017), Ben-David et al. (2018)), the literature on ETFs and underlying corporate debt securities has shown theoretically and empirically that the illiquid and hard-to-access nature of these securities imposes limits to arbitrage and can lead to persistent price distortions (Pan and Zeng (2017), Bhattacharya and O'Hara (2018), Todorov (2021)). This weakens the information link, leading liquidity traders to migrate from the underlying corporate debt securities to the ETFs which offer lower transaction and adverse selection costs (Dannhauser, 2017). As a result, we hypothesize that the ETFs will have stronger effects on the underlying equities than on the corporate debt securities.

We start our empirical analysis by testing whether ETFs propagate liquidity shocks to the underlying securities based on the theoretical framework of Cespa and Foucault (2014). The authors argue that the presence of information links can lead to illiquidity contagion when investors are unable to price one asset due to the illiquidity of the other, citing the dry-up of liquidity of ETFs during the 2010 flash crash as an example. Arbitrageurs can dampen this effect by providing capital to both assets but their absence can exacerbate the liquidity dry-up. We find that a one-standard-deviation increase in ETF bid-ask spreads is associated with a next-day increase in equities' bid-ask spreads of 1.3 basis points (bps). However, debt securities' bid-ask spreads are not affected by a change of ETF bid-ask spreads. Furthermore, we find that arbitrage activity plays an active role in reducing illiquidity contagion between ETFs and equities by 0.7 bps due to the provision of arbitrage capital in both assets, but not so between ETFs and debt securities where arbitrageurs are less active.

The results are consistent with the two market setups outlined in the theoretical framework of Cespa and Foucault (2014): in a fully interconnected market the liquidity of the two assets is interrelated through the information channel, while in a fully segmented market there are no liquidity spillovers. These two theoretical setups represent the opposite ends of a spectrum, and our empirical results suggest that ETFs lie within these two extremes. On the one hand, ETFs and the underlying equities are closer to the fully interconnected market where investors use information from each asset to price the other (strong information link). On the other hand, ETFs and the underlying corporate debt securities are closer to the fully segmented market where investors largely ignore the information present in asset prices because it can be noisy, so a deterioration of liquidity in one asset does not have cross-asset effects (weak information link).

In the second part of our analysis, we investigate the effect of ETF demand shocks on the underlying securities' returns. If the assets are closely linked, the theoretical framework of Cespa and Foucault (2014) predicts that demand shocks in one asset can have an impact on the price of the other asset. This can occur through the information channel when investors revise their views on the price of one asset after observing a change in the price of the other asset, or through the arbitrage channel when arbitrageurs propagate the price shock by trading both assets. However, when the markets are fully segmented such an effect does not exist. We estimate regressions of daily security returns on security-level ETF flows, which proxy the expected demand for each security caused by aggregate additional ETF demand, in order to establish whether changes in ETF demand affect the underlying returns. We find that a one-standard-deviation increase of lagged ETF flows is associated with a 14.9 bps increase of daily stock returns but only 0.4 bps increase of daily debt securities' returns. Furthermore, we find that this effect is almost exclusively driven by arbitrageurs, which highlights their important role in ETF markets. The results show that ETF demand affects equities' prices more strongly than debt securities' prices, consistent with our argument of an interconnected market between ETFs and equities but a segmented one between ETFs and corporate debt securities.

Finally, we look at the effect of ETF ownership, i.e. the fraction of the underlying securities' market capitalisation owned by ETFs, on the volatility of the securities. If ETF ownership facilitates arbitrage between ETFs and the underlying securities, the two markets become more interconnected and the activity on the underlying securities increases, with a subsequent increase in their volatility (Ben-David et al., 2018). In contrast, if the underlying assets are hard-to-trade, a higher ETF ownership is associated with a migration of liquidity traders from the underlying assets to the ETFs due to the latter's higher accessibility (Dannhauser, 2017). This segments the markets and lowers activity in the underlying assets and hence their volatility (Grossman, 1989). We thus expect that higher ETF ownership is associated with an increase of equities' volatility but a decrease of debt securities' volatility. Consistent with this prediction, we find that a one-standard-deviation increase in ETF ownership is associated with an increase of equities' volatility by 1% of a standard deviation but a decrease of debt securities' volatility by 1% of a standard deviation.

Against the backdrop of a significant growth of ETFs over the past decade, our results have important policy implications. First, the accessibility of the underlying markets and by extension the formation of information links and ease with which investors can exploit arbitrage opportunities is an important factor in determining whether ETFs can propagate shocks to them. Second, ETFs can affect the securities they invest in via various channels including their liquidity, prices as well as volatility, and understanding the underlying mechanism that drives the effects on these channels is crucial in providing a holistic view of how ETFs can transmit shocks. For example, the regulatory report on the events of the flash crash of 2010 describes the propagation of liquidity shocks from ETFs to the underlying equities due to a deterioration of information available in the former to price the latter (CFTC-SEC, 2010). More recently in the market turmoil of March 2020 due to Covid-19, ETFs acted as price discovery mechanisms for the underlying corporate debt securities and traded at large discounts as the demand shocks hitting ETF shares were not being transmitted to the illiquid underlying securities (BoE (2020b), Aramonte and

Avalos (2020)). These events are consistent with our results and our proposed mechanism of information links and arbitrage activity driving ETF behaviour.

Our paper contributes to the literature on links between assets. King and Wadhwani (1990) argue that asset prices are linked via information channels, which partly explains their simultaneous drop during the market crash of 1987. Duffie et al. (2014) show theoretically the existence of strategic complementarities in information acquisition in segmented markets. They also show cross-class externalities, including pure learning externalities between linked markets. Rahi and Zigrand (2009) show theoretically how arbitrageurs integrate markets by exploiting asset mispricings. We examine the effects of such links in the context of ETFs and the underlying markets.

We also contribute to the literature on illiquidity contagion. When arbitrage capital becomes scarce, prices can deviate significantly from their fundamental values (Hu et al., 2013). We empirically test the theoretical predictions of Cespa and Foucault (2014) by investigating whether liquidity shocks can propagate from ETFs to the underlying securities, and the role of arbitrageurs in mitigating this effect.

Finally, our paper is related to the growing literature on ETFs and how they affect asset prices. Da and Shive (2015) document the positive association between ETF ownership and return comovement of underlying stocks due to arbitrage while Agarwal et al. (2017) document a similar pattern with the liquidity of the underlying stocks. Evans et al. (2017) find a positive relationship between ETF ownership and bid-ask spreads of the underlying stocks. Bhattacharya and O'Hara (2018) show theoretically that ETFs investing in hard-to-access markets such as corporate bonds can transmit noise and form weak information links while Pan and Zeng (2017) show theoretically and empirically that the illiquidity of corporate bond markets limits arbitrage opportunities with ETFs. Glosten et al. (2020) show that ETFs increase the informational efficiency of the underlying stocks by incorporating systematic information faster and transmitting it to the underlying securities. Bae and Kim (2020) find that ETF tracking errors are positively correlated with the illiquidity of the underlying securities. Ben-David et al. (2018) argue that ETF ownership increases the non-fundamental volatility of underlying stocks, adding an undiversifiable risk which increases their risk premia. In contrast, Agapova and Volkov (2018) find that ETF ownership reduces the volatility of the underling bond securities. We propose the presence of information links and accessibility of the securities as an explanation behind the different effects of ETFs to the underlying equities and corporate debt securities.

The rest of the paper is structured as follows. Section 3.2 provides the ETF institutional details, section 3.3 describes the data used in this study, section 3.4 presents the empirical results and section 3.5 concludes.

3.2 Institutional Details

ETFs are investment companies that track the performance of a securities index, similarly to index mutual funds. The main difference is that ETFs allow their shares to be traded continuously intradaily on an exchange. ETFs can replicate an index either by holding all or a representative sample of the securities comprising the index (physical ETFs) or by entering into derivatives contracts, usually total return swaps, where the return on the index is swapped with the return on another benchmark (synthetic ETFs). Other types of ETFs also exist, such as leveraged ETFs that attempt to deliver a multiple of the index return, and inverse ETFs that seek to deliver the inverse of the index return.

ETF shares can be created and redeemed like other open-ended funds. However, this can only be done by a select group of market participants called authorised participants (APs), who have a legal agreement with the ETFs to trade directly with them. The APs do this because they can profit from bid-ask spreads on the secondary market and by creating and redeeming ETF shares when their value deviates from the net asset value (NAV) of the underlying securities. The trading of shares between the APs and the ETF in exchange for the underlying securities or cash constitutes the primary market. Other market participants trade ETF shares on an exchange or over-the-counter through market makers (which can also be APs), which constitutes the secondary market. The secondary market trading allows the ETF share price to move even in the absence of fund flows.

The continuous trading of ETF shares ensures that their price does not deviate significantly from the underlying NAV. If there is a positive demand shock on the ETF shares such that they trade at a premium relative to the NAV, the APs can buy the underlying securities at the NAV, submit them to the ETF in order to create new ETF shares on the primary market and sell them for a profit on the secondary market. This creates an upward pressure on the underlying securities and a downward pressure on the ETF shares until prices converge. Conversely, when a negative demand shock causes the ETF shares to trade at a discount relative to the NAV, the APs can buy the shares on the secondary market and redeem them on the primary market in exchange for the underlying securities, which can be subsequently sold at the NAV for a profit. This creates a downward pressure on the underlying securities and positive pressure on the ETF shares. ETF arbitrage can also be achieved by other market participants on the secondary market by buying the inexpensive asset and short selling the expensive one until prices converge for a profit. Of course, this mechanism is not a pure arbitrage opportunity as prices may not converge fast enough. Through this arbitrage mechanism, demand shocks on ETF shares can propagate to the underlying securities.

While there also exist other products such as index mutual funds that contain systematic information regarding the underlying assets, and could also create information links with them, ETFs are unique in allowing continuous trading of their shares rather than only once per day. Hence, they are more suitable for speculative and hedging purposes which fosters the creation of information links.

3.3 Data

We use a proprietary dataset on Irish-domiciled ETFs and their holdings from the Central Bank of Ireland (CBI) database.[2] All funds report their holdings to the CBI on a quarterly basis and are categorised internally into the following types according to their investment strategy: equity, bond, hedge, mixed, money market (MM), real estate (RE) and other funds. An ETF can belong to any of these types, although in practice the vast majority are either equity or bond funds. As of September 2018, there were 694 Irish-domiciled ETFs holding a total of EUR 424 billion of assets, which is around two-thirds of the total

[2] https://www.centralbank.ie/docs/default-source/statistics/statistical-reporting-requirements/fund-administrators/money-market-and-investment-funds-return-(mmif)/mmif-notes-on-compilation.pdf

held by euro area ETFs. The prominence of Ireland as an ETF hub in the euro area is mainly attributed to its robust regulatory framework for investment funds and business-friendly environment. The majority of these assets was invested in physical ETFs (EUR 374 billion), and EUR 271 billion was invested in equities while EUR 116 billion was invested in bonds. Together, equities and bonds comprised more than 90% of total assets held by Irish ETFs.

Our equities sample covers the period from March 2014, the earliest available date for which reliable data exist, up to December 2018. We have a total of 16,937 equities held by Irish ETFs at various points during the sample period. We use Bloomberg to download data for each stock. We obtain daily data on price, shares outstanding, volume, percentage bid-ask spread, total assets, book value of debt, revenue, cost of goods sold, as well as bid and ask percentage volumes to identify the direction of trades. We use this data to construct the main variables as well as controls.

Moving to corporate debt securities, we obtain daily data on their individual characteristics from IHS Markit including mid price, bid-asks-spread, maturity date, number of trades and volume. Credit ratings data is obtained from the CBI database and is mapped to a scale from 1 (highest rating) to 22 (lowest rating) following Dimitrov et al. (2015). The sample covers the period from January 2016, the earliest available date in the Markit database, up to December 2018. We have a total of 22,534 corporate debt securities held by the Irish ETFs during this period. We provide details on the construction of the variables in Appendix B.1.

Table 3.1 reports the amounts invested in equities and debt securities by Irish ETFs per country of security as of September 2018. Only the five largest countries according to amount invested are shown. The table also reports the amount held in each country as a percentage of total assets and the amount invested as a percentage of the total market capitalisation (equities) or amount outstanding (debt securities) of the country. Amounts are in EUR million.

As can be seen, 50% of total assets held in equities or EUR 136 billion are invested in US equities, followed by UK, Japan, Germany and France with smaller fractions. Irish ETFs hold on average 0.5% of the total market capitalisation of each country. For corporate debt securities, 35% of total assets or EUR 23 billion are invested in US debt, followed by

Table 3.1: Amounts invested by Irish ETFs in equities and debt securities per country of security in EUR million

Country	Amount	% of total assets	% of country market cap
Panel A: Equities			
US	136,150	50.16	0.49
UK	18,324	6.75	0.59
Japan	18,020	6.64	0.34
Germany	15,438	5.69	0.82
France	12,501	4.06	0.55
Panel B: Corporate debt securities			
US	23,006	34.96	0.11
UK	6,923	10.52	0.25
France	6,474	9.84	0.32
Netherlands	6,393	9.72	0.41
Germany	3,572	5.43	0.23

UK, France, the Netherlands and Germany. On average, Irish ETFs hold 0.3% of the total amount outstanding of debt issued by entities in each country.

Table 3.2 provides summary statistics for the variables that we use in the analysis. Panels A and B present summary statistics for the monthly equities and debt securities samples while panels C and D present the statistics for the daily equities and debt securities samples.

Looking at Panel A, we observe that the daily stock volatility, calculated as the standard deviation of daily stock returns over the period of a month, has a maximum value in our sample of 94.914%. Such high values reflect the fact that we include all the equities holdings and do not confine our analysis to US equities which are not as volatile.[3] ETF ownership of equities ranges from -0.170% (a negative value indicates short positions) to 23.200%, almost a quarter of a stock's market capitalisation. Hedge funds have the largest short position (-21.097%) while equity funds have the largest long position (38.580%).

In Panel B, daily volatility of corporate debt securities can similarly take high values up to 99.410%, although the highest ETF ownership is lower compared to equities at 14.649%. In addition, there are no short ETF positions on debt securities as observed by

[3] We have repeated our analysis by removing the outliers of the variables of interest to ensure that our analysis is robust.

the minimum value of ETF ownership of 0%. Hedge funds again have the largest short position (-4.504%) while bond funds have the largest long position (27.383%), both smaller than the corresponding positions for equities.

Moving to Panel C, the stock-level ETF flows, a weighted average of the daily flows occurring in all ETFs investing in each security, take values from EUR -42.522 million to EUR 45.851 million. Stock-level ETF bid-ask spreads range from -0.003% to 2.789%. ETF mispricing, the difference between ETFs' share price and the underlying portfolio's NAV, ranges from EUR -0.001 million to EUR 1246.021 million.

In Panel D, corporate debt ETF flows range from EUR -5.928 million to EUR 5.737 million, lower than for equities which reflects the reduced arbitrage activity. ETF bid-ask spreads range from 0% to 0.842% while ETF mispricing ranges from EUR 0 to EUR 138.017 million.

3.4 Empirical analysis

3.4.1 ETFs and illiquidity contagion

We begin our analysis by investigating the potential of ETFs to transmit liquidity shocks to the underlying securities. We test our hypothesis that the magnitude of illiquidity spillover will be stronger from ETFs to the underlying equities than to the underlying debt securities using the theoretical framework of Cespa and Foucault (2014). The authors argue that the magnitude of illiquidity spillover is determined by the strength of the information link, the presence of arbitrage capital and the dealers' risk tolerance. While the framework allows for the possibility that the underlying securities could also affect ETFs, we focus on one side of the relationship because ETFs attract high-frequency trading and thus can incorporate information faster than the underlying securities, especially when the latter are hard-to-trade (Aramonte and Avalos, 2020). This can result in ETFs affecting the underlying securities rather than the other way around (Bhattacharya and O'Hara, 2018).

Our measure of liquidity is the bid-ask spread. The bid-ask spreads as provided by Bloomberg and IHS Markit are calculated based on observed trades throughout each day.

Table 3.2: Summary statistics

Summary statistics for the variables used in the study. Columns denote, respectively, the name of the variable, number of observations, mean value, standard deviation, minimum value, 25th, 50th, 75th percentiles and maximum value.

Variable	*N*	Mean	SD	Min	25th	50th	75th	Max
Panel A: Monthly sample (equities)								
Daily stock volatility (%)	602,961	2.245	1.583	0.000	1.377	1.900	2.665	94.914
ETF ownership (%)	615,173	0.071	0.193	−0.170	0.000	0.000	0.061	23.200
Equity fund ownership (%)	615,173	0.327	0.774	−1.826	0.000	0.026	0.330	38.580
Hedge fund ownership (%)	615,173	0.021	0.208	−21.097	0.000	0.000	0.000	9.700
MM fund ownership (%)	615,173	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mixed fund ownership (%)	615,173	0.027	0.199	−0.522	0.000	0.000	0.003	20.998
Bond fund ownership (%)	615,173	0.000	0.030	−0.081	0.000	0.000	0.000	9.507
Other fund ownership (%)	615,173	0.003	0.140	−0.302	0.000	0.000	0.000	30.300
RE fund ownership (%)	615,173	0.003	0.114	−0.009	0.000	0.000	0.000	18.827
Log(Market Cap (EUR million))	615,173	8.033	9.161	−3.577	5.824	6.793	7.831	12.982
1/Price	615,173	3.086	108.677	0.000	0.051	0.152	0.744	20000.000
Amihud ratio (%)	615,173	0.001	0.103	0.000	0.000	0.000	0.000	44.289
Bid-ask spread (%)	613,940	0.603	1.883	0.004	0.142	0.258	0.522	179.605
Book-to-market	615,173	1.494	2.603	0.000	0.591	1.004	1.539	140.345
Past 12-month returns (%)	615,173	15.404	70.624	−99.957	−15.034	5.358	30.240	8487.126
Gross profitability	615,173	0.163	0.331	−69.369	0.030	0.083	0.206	9.465

Table 3.2: Summary statistics (continued)

Variable	N	Mean	SD	Min	25th	50th	75th	Max
Panel B: Monthly sample (corporate debt)								
Daily debt volatility (%)	548,609	0.278	0.539	0.000	0.079	0.177	0.350	99.410
ETF ownership (%)	548,609	0.216	0.558	0.000	0.000	0.000	0.107	14.649
Equity fund ownership (%)	548,609	0.001	0.023	0.000	0.000	0.000	0.000	5.761
Hedge fund ownership (%)	548,609	0.014	0.201	−4.504	0.000	0.000	0.000	18.981
MM fund ownership (%)	548,609	0.008	0.233	0.000	0.000	0.000	0.000	19.599
Mixed fund ownership (%)	548,609	0.072	0.352	−0.109	0.000	0.000	0.000	16.263
Bond fund ownership (%)	548,609	0.570	1.552	−0.510	0.000	0.000	0.333	27.383
Other fund ownership (%)	548,609	0.026	0.227	−2.280	0.000	0.000	0.000	15.992
RE fund ownership (%)	548,609	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Credit rating	539,598	7.985	3.730	1.000	6.000	8.000	10.000	22.000
Time to maturity	548,609	9.619	13.760	0.000	2.875	5.249	9.032	99.775
Age	548,609	4.057	3.579	0.019	1.561	3.129	5.353	32.493
Log(Amount outstanding (EUR million))	547,638	20.392	20.115	11.025	19.807	20.125	20.592	23.588
Bond zero	548,609	0.659	0.380	0.000	0.273	0.857	1.000	1.000
Log(Trades)	548,609	4.014	4.885	0.000	0.000	1.609	3.989	8.889
Amihud ratio (%)	303,413	0.000	0.000	0.000	0.000	0.000	0.000	0.170
Bid-ask spread (%)	548,609	0.534	2.863	0.000	0.186	0.351	0.639	198.020
Turnover	547,638	0.003	0.385	0.000	0.000	0.000	0.002	132.124
Log(Average trade size)	303,413	13.238	13.360	6.908	11.986	12.794	13.462	15.425

Table 3.2: Summary statistics (continued)

Variable	N	Mean	SD	Min	25th	50th	75th	Max
Panel C: Daily sample (equities)								
Security-level ETF flows (EUR million)	12,780,975	0.003	0.109	−42.522	0.000	0.000	0.000	45.851
Security-level ETF bid-ask spread (%)	12,780,975	0.008	0.028	−0.003	0.000	0.001	0.005	2.789
Ret[$t, t-1$] (%)	12,240,572	0.038	2.713	−99.327	−1.104	−0.004	1.098	450.291
Log(Market Cap (EUR million))	12,780,975	8.036	9.169	−3.699	5.823	6.794	7.833	13.048
1/Price	12,780,975	3.061	108.908	0.000	0.050	0.149	0.724	25000.000
Amihud ratio (%)	12,204,888	0.001	0.393	0.000	0.000	0.000	0.000	781.250
Bid-ask spread (%)	12,675,871	0.564	1.706	0.004	0.140	0.255	0.510	197.563
Book-to-market	12,665,539	1.499	3.845	0.000	0.589	1.001	1.536	1872.746
Past 12-month returns (%)	12,780,975	15.688	70.851	−99.957	−14.909	5.510	30.556	8643.620
Gross profitability	12,662,938	0.164	0.360	−69.369	0.030	0.084	0.207	31.230
Order imbalance	12,580,958	−0.006	0.330	−158.702	−0.046	−0.002	0.035	209.540
ETF mispricing (EUR million)	12,780,975	0.201	5.448	−0.001	0.000	0.001	0.009	1246.021
FD	11,322,719	0.751	0.159	0.116	0.651	0.854	0.874	0.937

Table 3.2: Summary statistics (continued)

Variable	N	Mean	SD	Min	25th	50th	75th	Max
Panel D: Daily sample (corporate debt)								
Security-level ETF flows (EUR million)	12,137,327	0.001	0.034	−5.928	0.000	0.000	0.000	5.737
Security-level ETF bid-ask spread (%)	12,137,327	0.001	0.004	0.000	0.000	0.000	0.001	0.842
Ret$[t, t-1]$ (%)	12,913,942	0.004	1.334	−99.507	−0.082	0.000	0.085	1934.592
Credit rating	12,549,641	7.971	3.717	1.000	6.000	8.000	10.000	22.000
Time to maturity	12,913,942	9.626	13.711	0.000	2.932	5.284	9.079	100.005
Age	12,913,942	3.958	3.574	0.000	1.457	3.047	5.270	32.554
Log(Amount outstanding (EUR million))	12,891,097	20.390	20.115	11.025	19.807	20.119	20.592	23.588
Bond zero	12,913,942	0.661	0.379	0.000	0.273	0.864	1.000	1.000
Log(Trades)	12,913,942	4.003	4.890	0.000	0.000	1.609	3.970	9.325
Amihud ratio (%)	5,977,483	0.000	0.018	0.000	0.000	0.000	0.000	10.988
Bid-ask spread (%)	12,913,942	0.542	2.894	0.000	0.192	0.356	0.649	198.020
Turnover	12,891,097	0.004	0.574	0.000	0.000	0.000	0.002	298.550
Log(Average trade size)	7,090,874	13.266	13.381	6.908	12.007	12.825	13.495	15.425
ETF mispricing (EUR million)	12,137,327	0.058	0.754	0.000	0.000	0.001	0.007	138.017
FD	12,342,449	0.807	0.113	0.053	0.765	0.874	0.874	0.937

We define the security-level ETF bid-ask spread as follows:

$$ETF\ bid - ask\ spread_{i,t} = \sum_{j=1}^{J} w_{i,j,t} bid - ask\ spread_{j,t} \tag{3.4.1}$$

where J is the set of ETFs that hold the security i, $w_{i,j,t}$ is the weight of security i in the portfolio of ETF j in day t, and $bid - ask\ spread_{j,t}$ is the bid-ask spread of ETF j in day t. The weights do not sum to 1 for each security but they represent the "information proportionality" of each ETF. As an example, a hypothetical ETF that invests 99% of its assets on a specific security should have a price that closely mirrors that of the security, and investors would assign a large weight on its informativeness. As a result, the ETF's bid-ask spread is weighted accordingly to capture the impact of a decrease of its liquidity on the underlying security's liquidity due to the breakdown of the information link, depending on how informative the ETF's price is.

We proxy the degree of arbitrage activity by constructing the security-level ETF mispricing variable following Ben-David et al. (2018).

$$ETF\ mispricing_{i,t} = \frac{\sum_{j=1}^{J} w_{i,j,t} AUM_{j,t} \mid Mispricing_{j,t} \mid}{MktCap_{i,t}} \tag{3.4.2}$$

where J is the set of ETFs that hold the security i, $w_{i,j,t}$ is the weight of security i in the portfolio of ETF j in day t, $AUM_{j,t}$ are the total assets of ETF j in day t, and $MktCap_{i,t}$ is the market capitalisation of security i in day t. $\mid Mispricing_{j,t} \mid$ denotes the difference between the ETF j's share price and NAV divided by its share price in day t. Larger mispricing indicates the absence of arbitrageurs in the market that exploit the price differences. We create a dummy variable that takes the value of 1 for values of ETF mispricing higher than the 90th percentile and interact it with the ETF bid-ask spread in order to estimate the effect of high mispricing (absence of arbitrageurs) on illiquidity contagion.

In addition, we measure dealers' risk tolerance by using the VIX index for equities and the MOVE index for debt securities as a proxy of market stress. As Cespa and Foucault (2014) argue, higher market stress implies a lower risk tolerance of dealers, which strengthens illiquidity contagion. Similarly to mispricing, we create dummy variables that take the value of 1 for values of the corresponding variables higher than the 90th percentile and interact them with the ETF bid-ask spread.

In our regressions we include security and day fixed effects, and standard errors are clustered at the country and day levels. Furthermore, we include a number of lagged control variables. For equities we include, following Ben-David et al. (2018), market capitalisation, the inverse of the stock price as a measure of size, the Amihud (2002) measure and the bid-ask-spread to account for persistence in illiquidity. In addition, we include a number of control variables that are standard predictors of returns, including the book-to-market ratio, the cumulative past 12-month returns and gross profitability. Finally, we include order imbalance which is calculated as the euro value of buy minus sell trades divided by market capitalisation. For debt securities we include as control variables the credit rating, time to maturity, the percentage of days in a month that the security didn't trade (Bond zero), the bid-ask spread and the security's turnover defined as the average daily volume over a month as a percentage of its amount outstanding. We omit the amount outstanding because it remains constant for each security and is collinear with the security fixed effects.[4]

The results for equities and debt securities are presented in Tables 3.3 and 3.4 respectively. We use lagged ETF bid-ask spread in order to avoid simultaneity bias as both assets could influence each other. In column (1) we present results without including the stress index (VIX or MOVE) or mispricing interactions, in column (2) we include the stress index interaction, in column (3) we include the mispricing interaction while in column (4) we include all interactions.

Looking at column (3) of Table 3.3, the effect of the information channel on illiquidity contagion is given by the sum of the coefficients of ETF bid-ask spread and its interaction with ETF mispricing, which rules out the effect of the arbitrage channel as it controls for the absence of arbitrageurs. We thus document an increase of 1.3 (= 0.6 + 0.7) bps of bid-ask spreads for a one-standard-deviation increase of ETF bid-ask spreads, which provides

[4] In unreported results we also included as control variables the Amihud measure of illiquidity, the logarithm of the number of trades per month and the average trade size over a month. However, the inclusion of these controls greatly reduces our sample size due to limited observations of these variables. We ran the regressions in the reduced sample with and without these controls and the results for our variables of interest did not change. As such, we do not include them in the final regressions in order to preserve our sample size.

evidence for illiquidity contagion. The positive coefficient of ETF mispricing shows that the absence of arbitrageurs exacerbates the liquidity dry-up of both assets, and is consistent with the arguments of Cespa and Foucault (2014) since arbitrageurs dampen illiquidity contagion by providing capital to both assets. When looking at the full model specification in column (4) this relationship is further dampened during times of high market stress as indicated by the negative VIX interaction coefficient of -0.4 bps. This is in contrast to the theoretical predictions of Cespa and Foucault (2014), who argue that low dealer risk tolerance (as proxied by high values of the VIX index) exacerbates illiquidity contagion. A potential driver behind this result could be that the dealers who specialise in one asset and propagate liquidity shocks when the informativeness of the other asset evaporates coexist with dealers who trade both assets for hedging purposes.[5] These dealers could then shift their capital to the underlying securities when ETFs become illiquid, dampening illiquidity contagion.

Moving to debt securities, we do not observe a significant relationship between ETF bid-ask spreads and debt securities' bid-ask spreads.[6] Furthermore, ETF mispricing is not significant, indicating that arbitrage activity does not affect illiquidity contagion between ETFs and debt securities. The MOVE interaction coefficient is similarly insignificant. Overall, the findings indicate the presence of a strong information link between ETFs and equities which increases the interconnectedness of the market and the potential for illiquidity contagion, but a weaker link between ETFs and debt securities which segments the market and reduces contagion effects.

In Appendix B.2 we provide results using alternative thresholds of 70th and 80th percentiles for the stress indices and ETF mispricing. While the results for debt securities remain insignificant (Tables B.4 - B.5), we observe that for equities ETF mispricing is 0.1 bps insignificant when we use the 70th percentile (Table B.2 column (3)) and 0.4 bps significant

[5]In their model, Cespa and Foucault (2014) assume that dealers specialise in one asset, so they infer its price using information from the other asset (cross-asset learning). This enables illiquidity contagion when the informativeness of the other asset evaporates and excludes cross-market hedging effects when dealers diversify their risk by trading both assets. The cross-market hedgers are distinct from the arbitrageurs as defined in our paper who trade assets to exploit mispricing opportunities rather than hedge their positions that result from market intermediation.

[6]All our results hold if we also include government debt securities which represent only a small fraction of total debt securities that Irish ETFs invest in.

when we use the 80th percentile (Table B.3 column (3)), so its magnitude increases as the threshold becomes higher. The overall effect of illiquidity contagion also increases, from 1.1 bps to 1.3 bps. This result shows that illiquidity contagion between ETFs and equities is directly linked to the level of arbitrage activity: as arbitrageurs increasingly exit the market, the dampening effect is reduced and illiquidity contagion increases.

Finally, looking at the VIX interaction coefficients in column (4), we observe that they become smaller in absolute magnitude as the threshold becomes higher, from -0.9 bps and -0.6 bps to -0.4 bps for the 70th, 80th and 90th percentiles respectively. This indicates that the ability of dealers to dampen illiquidity contagion through cross-asset trading becomes increasingly impaired due to their decreasing risk tolerance and withdrawal from the market as it becomes more volatile.

3.4.2 ETF flows and returns

The previous results indicate that ETFs and equities form strong information links while ETFs and debt securities form weak ones, with implications for liquidity commonality. In this section we assess the effects of ETFs on the underlying securities' returns in order to further analyse the implications of the information and arbitrage channels. Cespa and Foucault (2014) predict that in a fully interconnected market demand shocks on one asset can affect the price of the other while in a fully segmented market they do not. Hence, we expect a stronger effect of ETF demand shocks on equities' returns than on debt securities' returns. This can occur through cross-asset learning as investors revise their beliefs about one asset by observing shocks in the other asset, as well as through arbitrage trading of both assets. As explained in section 3.2, the APs can transmit demand shocks to the underlying securities through the creation and redemption of ETF shares. Following Ben-David et al. (2018), we construct the security-level ETF flows variable which acts as a proxy for ETF demand shocks:

$$ETF\ flows_{i,t} = \frac{\sum_{j=1}^{J} w_{i,j,t} Flows_{j,t}}{Volume_{i,t}} \tag{3.4.3}$$

where J is the set of ETFs that hold the security i, $w_{i,j,t}$ is the weight of security i in the

Table 3.3: ETF bid-ask spreads and stock bid-ask spreads

This table reports estimates from OLS regressions of daily stock bid-ask spreads on ETF bid-ask spreads and control variables. ETF bid-ask spreads are divided by market capitalisation and standardised. VIX and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 90th percentile. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from March 2014 to December 2018.

Dependent Variable:	Bid-ask spread (t)			
	(1)	(2)	(3)	(4)
ETF bid-ask spread ($t-1$) (%)	0.012***	0.013***	0.006***	0.008***
	(3.072)	(3.383)	(2.864)	(3.078)
ETF bid-ask spread (%) * VIX ($t-1$)		−0.004***		−0.004***
		(−4.994)		(−4.032)
ETF bid-ask spread (%) * ETF mispricing ($t-1$)			0.007***	0.007***
			(5.774)	(5.720)
log(MktCap ($t-1$))	−0.002***	−0.002***	−0.002***	−0.002***
	(−3.389)	(−3.388)	(−3.384)	(−3.384)
1/Price ($t-1$)	0.000	0.000	0.000	0.000
	(0.834)	(0.849)	(0.836)	(0.849)
Amihud ratio ($t-1$)	0.111***	0.111***	0.111***	0.111***
	(2.796)	(2.797)	(2.797)	(2.797)
Bid−ask spread ($t-1$)	0.576***	0.576***	0.576***	0.576***
	(15.478)	(15.477)	(15.481)	(15.481)
Book-to-market ($t-1$)	0.000***	0.000***	0.000***	0.000***
	(10.348)	(9.330)	(10.348)	(9.508)
Past 12-month returns ($t-1$)	0.000*	0.000*	0.000*	0.000*
	(1.830)	(1.807)	(1.819)	(1.770)
Gross profitability ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.418)	(−0.345)	(−0.385)	(−0.235)
Order imbalance ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.655)	(−0.620)	(−0.656)	(−0.642)
Ret[$t-1, t-2$]	0.000	0.000	0.000	0.000
	(0.352)	(0.353)	(0.353)	(0.354)
Intercept	0.018***	0.018***	0.018***	0.018***
	(3.712)	(3.712)	(3.707)	(3.707)
Day fixed effects	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes
Observations	11,411,458	11,411,458	11,411,458	11,411,458
R^2	0.566	0.566	0.566	0.566

Table 3.4: ETF bid-ask spreads and debt securities bid-ask spreads

This table reports estimates from OLS regressions of daily debt securities bid-ask spreads on ETF bid-ask spreads and control variables. ETF bid-ask spreads are divided by market capitalisation and standardised. MOVE and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 90th percentile. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from January 2016 to December 2018.

Dependent Variable:	Bid-ask spread (t)			
	(1)	(2)	(3)	(4)
ETF bid-ask spread ($t-1$) (%)	-0.000	-0.000	-0.001	-0.001
	(-1.482)	(-1.523)	(-1.348)	(-1.376)
ETF bid-ask spread (%) * MOVE ($t-1$)		0.000		0.000
		(0.259)		(0.254)
ETF bid-ask spread (%) * ETF mispricing ($t-1$)			0.000	0.000
			(1.063)	(1.058)
Credit rating ($t-1$)	0.000***	0.000***	0.000***	0.000***
	(3.674)	(3.674)	(3.675)	(3.675)
Bid-ask spread ($t-1$)	0.954***	0.954***	0.954***	0.954***
	(57.249)	(57.249)	(57.249)	(57.249)
Time to maturity ($t-1$)	0.000	0.000	0.000	0.000
	(1.067)	(1.067)	(1.067)	(1.067)
Bond zero ($t-1$)	-0.000***	-0.000***	-0.000***	-0.000***
	(-3.044)	(-3.045)	(-3.045)	(-3.045)
Turnover ($t-1$)	-0.000	-0.000	-0.000	-0.000
	(-0.664)	(-0.668)	(-0.562)	(-0.566)
Ret[$t-1, t-2$]	-0.057**	-0.057**	-0.057**	-0.057**
	(-2.416)	(-2.416)	(-2.416)	(-2.416)
Intercept	-0.001	-0.001	-0.001	-0.001
	(-0.984)	(-0.984)	(-0.984)	(-0.984)
Day fixed effects	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes
Observations	11,698,589	11,698,589	11,698,589	11,698,589
R^2	0.961	0.961	0.961	0.961

portfolio of ETF j in day t, $Flows_{j,t}$ is the percentage change in shares outstanding of ETF j in day t and $Volume_{i,t}$ is the volume of security i in day t. $Flows_{j,t}$ and $Volume_{i,t}$ are multiplied by their corresponding prices in order to obtain euro security-level ETF flows.

First, we regress stock returns in day t on the lagged flows and the same control variables as before. The results are presented in Table 3.5. In order to disentangle the information from the arbitrage channel, we include the ETF mispricing interaction in column (3). We observe a statistically significant effect of lagged ETF flows on stock returns, with a one-standard-deviation change in ETF flows being associated with a 14.9 bps change in stock returns. Interestingly, the effect is almost entirely driven by arbitrage activity as the absence of arbitrageurs as proxied by ETF mispricing almost entirely negates the effect with a coefficient of -14.7 bps. As before, the sum of the coefficients isolates the effect of the information channel which is only 0.2 bps.

Next, we interact ETF flows with the VIX index, which proxies dealers' risk tolerance. We expect a negative relationship because during times of stress when the risk tolerance of the dealers weakens, the information link breaks down lowering the effect of ETF demand shocks. Consistent with this prediction, as seen in column (5) we find a negative interaction coefficient of -30.3 bps.[7]

Finally, we consider how the different levels of financial development of each country in our sample affect the relationship between ETF flows and underlying securities' returns. Specifically, we use data from the IMF Financial Development Index[8] in order to assess whether the unique market characteristics of each country have an effect on our results. The data measure various aspects of development of financial institutions and financial markets and are reported in annual frequency, ranging from 0 (lowest development) to 1 (highest development). We have experimented with all the variables in the dataset and our results are broadly consistent. Hence, we report results for the overall country financial development, including financial markets and institutions. We create the dummy variable FD that takes the value of 1 if financial development is higher than the median value of

[7] In order to exclude the possibility that the results are driven by indexing effects, i.e. the exclusion and inclusion of stocks in the major indices, we have repeated the analysis by removing all observations in the months when all major index rebalances occur. The results remain the same.

[8] `https://data.imf.org/?sk=F8032E80-B36C-43B1-AC26-493C5B1CD33B`

development of all countries in our sample and 0 otherwise and interact it with ETF flows.[9] The latest available year available for the IMF data is 2016, so we assume constant FD values as of 2016 since there is little variation across time.[10] As can be seen in column (5), the interaction is negative and significant (-53.3 bps) implying that equities in countries with high financial development are less affected by ETF demand shocks. This is intuitive as such markets are more efficient so the equities' prices better reflect their fundamental values from other sources of information and do not rely on ETFs as much.

In Table B.6 provided in Appendix B.3 we repeat the analysis for the five largest countries individually in order to assess whether the effects are consistent across different countries. Irish ETFs do not have a significant effect on US equities, which is intuitive given the size of the US stock market and the relatively small size of Irish ETFs. The only country with significant effects is France (4 bps).

Next, we repeat the analysis for corporate debt securities and present the results in Table 3.6. As can be seen in column (3), we document a small increase in securities' returns of 0.4 bps for a one-standard-deviation increase of lagged ETF flows. However, this is completely negated by the absence of arbitrageurs as indicated by the coefficient of -0.4 bps of ETF mispricing, implying that the information channel has no effect on price shock propagation between ETFs and corporate debt securities and providing further evidence for the weak information link between them. Looking at column (5) the interaction of ETF flows with the MOVE index is insignificant, indicating that the relationship is not affected by a change in the dealers' risk tolerance, which is intuitive given the segmented nature of the market. Finally, the FD interaction is insignificant, which is likely due to the fact that corporate debt securities are OTC traded and are not tied to specific geographical markets, irrespectively of their issuing country. Looking at the five largest individual countries in Table B.7 in Appendix B.3, we don't observe any significant effect of Irish ETF flows on them.

Overall, the results in both the full sample and the individual countries suggest that ETF demand shocks have a much larger effect on equities' than debt securities' returns,

[9] We have also performed the analysis by considering the mean development. The results are robust.

[10] Repeating the analysis for equities from 2014 to 2016 with time-varying FD values yields similar results.

which is mainly driven by the activity of arbitrageurs. The results provide further evidence towards the importance of accessibility for the propagation of shocks between markets.

3.4.3 ETF ownership and volatility

In this section we investigate whether ETF ownership affects the underlying securities' volatility. The introduction of a correlated asset in the market such as ETFs can increase trading activity in both assets due to arbitrage opportunities, hence increasing their volatility (Ben-David et al., 2018) and making the two markets more interconnected. On the other hand, if the new asset is more liquid and accessible, it may cause a migration of liquidity traders to the new asset which reduces activity in the illiquid asset and hence its volatility (Grossman, 1989), segmenting the two markets.

We follow Ben-David et al. (2018) and define ETF ownership of security i in month t as the sum of the value of holdings by all ETFs investing in the security, divided by the security's market capitalisation at the end of the month:

$$ETF\ ownership_{i,t} = \frac{\sum_{j=1}^{J} w_{i,j,t} AUM_{j,t}}{MktCap_{i,t}} \tag{3.4.4}$$

where J is the set of ETFs that hold the security i, $w_{i,j,t}$ is the weight of security i in the portfolio of ETF j in month t, $AUM_{j,t}$ are the total assets of ETF j in month t, and $MktCap_{i,t}$ is the market capitalisation of security i in month t. In other words, this variable is the fraction of the total market capitalisation of the security held by Irish ETFs.

Our dependent variable is the daily volatility of security i, calculated by estimating the standard deviation of daily security returns for each month. We include the usual control variables, as well as the percentage of the total stock market capitalisation held by each fund type except for money market funds which have no equity holdings. Finally, we include three lags of volatility to account for volatility clustering.

The results of the OLS regressions of daily stock volatility on ETF ownership are presented in Table 3.7. We report results for the entire sample as well as for the largest countries individually. We use fixed effects at the security and month levels as before. Standard errors are double-clustered at the country and month levels when the entire

Table 3.5: ETF flows and stock returns

This table reports estimates from OLS regressions of daily stock returns on ETF flows and control variables. ETF flows are divided by market capitalisation and standardised. VIX and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 90th percentile. FD is a dummy variable taking the value of 1 for values higher than its median. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from March 2014 to December 2018.

Dependent Variable:	Ret[$t, t-1$]				
	(1)	(2)	(3)	(4)	(5)
ETF flows ($t-1$) (%)	0.003***	0.003***	0.149***	0.479***	0.690***
	(3.393)	(3.799)	(12.877)	(3.199)	(3.853)
ETF flows (%) * VIX ($t-1$)		−0.224***			−0.303***
		(−3.383)			(−11.393)
ETF flows (%) * ETF mispricing ($t-1$)			−0.147***		−0.156***
			(−12.255)		(−10.142)
ETF flows (%) * FD ($t-1$)				−0.477***	−0.533***
				(−3.186)	(−3.083)
log(MktCap ($t-1$))	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***
	(−18.480)	(−18.451)	(−18.481)	(−18.481)	(−18.436)
1/Price ($t-1$)	0.000	0.000	0.000	0.000	0.000
	(1.461)	(1.462)	(1.460)	(1.460)	(1.071)
Amihud ratio ($t-1$)	0.291***	0.291***	0.291***	0.291***	0.291***
	(2.997)	(2.996)	(2.997)	(2.996)	(2.997)
Bid-ask spread ($t-1$)	−0.001	−0.001	−0.001	−0.001	−0.001
	(−0.171)	(−0.169)	(−0.178)	(−0.169)	(−0.172)
Book-to-market ($t-1$)	−0.000*	−0.000*	−0.000*	−0.000*	−0.000*
	(−1.828)	(−1.823)	(−1.828)	(−1.827)	(−1.793)
Past 12-month returns ($t-1$)	0.000**	0.000**	0.000**	0.000**	0.000**
	(2.255)	(2.244)	(2.255)	(2.254)	(2.220)
Gross profitability ($t-1$)	0.000	0.000	0.000	0.000	0.000
	(1.163)	(1.160)	(1.163)	(1.162)	(1.163)
Order imbalance ($t-1$)	0.000*	0.000*	0.000*	0.000*	0.000*
	(1.759)	(1.758)	(1.758)	(1.762)	(1.762)
Ret[$t-1, t-2$]	−0.016*	−0.016*	−0.016*	−0.016*	−0.016*
	(−1.845)	(−1.845)	(−1.845)	(−1.846)	(−1.847)
Intercept	0.019***	0.019***	0.019***	0.019***	0.019***
	(18.730)	(18.701)	(18.738)	(18.730)	(18.710)
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	11,415,066	11,415,066	11,415,066	11,415,066	11,415,066
R^2	0.092	0.092	0.092	0.092	0.093

Table 3.6: ETF flows and debt securities returns

This table reports estimates from OLS regressions of daily debt securities returns on ETF flows and control variables. ETF flows are divided by market capitalisation and standardised. MOVE and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 90th percentile. FD is a dummy variable taking the value of 1 for values higher than its median. Standard errors are double-clustered at the country and day levels. *t*-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from January 2016 to December 2018.

Dependent Variable:	Ret[$t, t-1$]				
	(1)	(2)	(3)	(4)	(5)
ETF flows ($t-1$) (%)	0.001	0.000	0.004***	0.004*	0.004**
	(0.835)	(0.706)	(9.539)	(1.915)	(2.566)
ETF flows (%) * MOVE ($t-1$)		0.001			0.000
		(1.648)			(0.269)
ETF flows (%) * ETF mispricing ($t-1$)			−0.004***		−0.004***
			(−9.846)		(−9.692)
ETF flows (%) * FD ($t-1$)				−0.003	0.001
				(−1.413)	(0.349)
Credit rating ($t-1$)	0.000	0.000	0.000	0.000	0.000
	(0.302)	(0.301)	(0.302)	(0.473)	(0.478)
Bid-ask spread ($t-1$)	0.002	0.002	0.002	0.002	0.002
	(0.731)	(0.731)	(0.730)	(0.729)	(0.728)
Time to maturity ($t-1$)	0.000	0.000	0.000	0.000	0.000
	(1.089)	(1.084)	(1.089)	(0.811)	(0.944)
Bond zero ($t-1$)	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	(−5.159)	(−5.159)	(−5.159)	(−5.076)	(−5.367)
Turnover ($t-1$)	0.000	0.000	0.000	0.000	0.000
	(0.391)	(0.318)	(0.026)	(0.231)	(0.033)
Ret[$t-1, t-2$]	−0.045***	−0.045***	−0.045***	−0.045***	−0.045***
	(−3.013)	(−3.013)	(−3.013)	(−3.002)	(−3.002)
Intercept	−0.000	−0.000	−0.000	−0.000	−0.000
	(−0.479)	(−0.479)	(−0.479)	(−0.555)	(−0.510)
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	11,698,589	11,698,589	11,698,589	11,161,001	11,161,001
R^2	0.020	0.020	0.020	0.020	0.020

sample is used, and at the security and month levels when individual countries are examined.

Looking at the results for the entire sample in column (All), we establish a positive relationship between ETF ownership and stock volatility. Specifically, for a one-standard-deviation increase of ETF ownership, stock volatility increases by 1% of a standard deviation. Examining individual countries, we infer that Irish ETFs do not affect the volatility of US stocks, but have a significant effect for UK (3.4%), Japanese (3.2%), German (5.3%) and French (7.0%) stocks.

In Table 3.8 we present the results of the same analysis using debt securities. In contrast to equities, we find that a one-standard-deviation increase of ETF ownership corresponds to a decrease of debt securities' volatility by 1% of a standard deviation. However, looking at individual countries, none of the five largest markets have a significant reduction of volatility although all coefficients are negative.

Our contrasting results for equities and debt securities corroborate the findings of the literature (Agapova and Volkov (2018), Ben-David et al. (2018)) and provide further evidence for the links between ETFs and the underlying securities. Increased arbitrage activity between ETFs and equities increases demand for the equities and their volatility and makes the two markets more interconnected. However, increased ETF ownership of debt securities incentivises liquidity traders to migrate from the debt securities to the ETFs (Dannhauser, 2017), which segments the two markets and lowers the underlying securities' volatility.

3.5 Conclusion

Our paper provides novel empirical evidence for the effects of information links and arbitrage activity between ETFs and their underlying securities. We investigate two underlying asset classes, equities and corporate debt securities, and document the heterogeneous effects of ETFs on their liquidity, returns and volatility.

First, we find that Irish ETFs propagate liquidity shocks to the underlying equities but not to the debt securities. Second, we document a stronger effect of ETF flows on the

Table 3.7: ETF ownership and stock volatility

This table reports estimates from OLS regressions of daily stock volatility on ETF ownership and control variables. In the (All) column estimates using the entire sample are presented, and in subsequent columns estimates are presented for the largest countries individually. The dependent variable and ETF ownership are standardised. Standard errors are double-clustered at the country and month levels for column (All), and security and month levels for subsequent columns. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from March 2014 to December 2018.

Dependent Variable:	Daily volatility (t)					
	(All)	(US)	(UK)	(Japan)	(Germany)	(France)
ETF ownership $(t-1)$	0.010**	0.005	0.034***	0.032**	0.053***	0.070***
	(2.091)	(0.885)	(3.290)	(2.111)	(2.973)	(3.239)
log(MktCap $(t-1)$)	−0.206**	−0.338***	−0.231***	−0.025	−0.067	−0.207**
	(−2.553)	(−12.097)	(−3.369)	(−0.537)	(−1.097)	(−2.145)
1/Price $(t-1)$	0.000	0.017***	−0.003	−0.159***	1.398**	1.804***
	(1.154)	(3.706)	(−0.703)	(−4.180)	(2.265)	(3.584)
Amihud ratio $(t-1)$	34.677**	151.919	−4.369*	−518200.397***	297.454	−14395.311
	(2.158)	(0.638)	(−1.859)	(−6.058)	(0.168)	(−0.814)
Bid-ask spread $(t-1)$	0.033***	0.011***	0.064*	0.269***	−0.038	0.060
	(3.674)	(2.980)	(1.716)	(3.234)	(−1.343)	(1.068)
Book-to-market $(t-1)$	0.007	0.003	0.012	0.003	0.003	0.000
	(1.105)	(0.205)	(0.841)	(0.554)	(0.189)	(0.011)
Past 12-month returns $(t-1)$	0.081**	0.002	−0.026	0.128***	0.152***	0.071
	(2.556)	(0.254)	(−1.043)	(7.142)	(2.708)	(1.115)
Gross profitability $(t-1)$	0.008	0.057	−0.163*	0.097	0.040	−0.234
	(0.616)	(1.602)	(−1.937)	(0.892)	(0.281)	(−0.776)
Equity fund ownership $(t-1)$	0.471	2.156*	1.376	0.806	0.135	2.721
	(0.723)	(1.803)	(1.518)	(1.488)	(0.079)	(1.324)
Hedge fund ownership $(t-1)$	−5.933*	−10.963***	3.559	0.476	5.183	−23.706**
	(−1.865)	(−4.351)	(0.899)	(0.232)	(1.447)	(−2.303)
Mixed fund ownership $(t-1)$	−0.013	−11.345***	10.333***	0.510	0.183	6.730
	(−0.011)	(−3.110)	(2.745)	(0.271)	(0.041)	(0.728)
Bond fund ownership $(t-1)$	−4.326	−10.642**	105.404**	114.190*	−77.760	−1330.493***
	(−0.633)	(−2.482)	(2.347)	(1.924)	(−0.459)	(−3.298)
Other fund ownership $(t-1)$	2.937	0.422	−0.029	14.249	1.777**	122.218
	(1.169)	(0.230)	(−0.007)	(0.931)	(2.183)	(1.371)
RE fund ownership $(t-1)$	−0.641	5.163	−24.177	54.889**	11.004	−16.749
	(−1.050)	(1.036)	(−1.472)	(2.183)	(0.516)	(−0.367)
Daily volatility $(t-1)$	0.212***	0.105***	0.185***	0.188***	0.177***	0.052
	(6.218)	(7.821)	(3.266)	(8.033)	(5.684)	(1.453)
Daily volatility $(t-2)$	0.101***	0.055***	0.065*	0.082***	0.084***	0.063**
	(11.100)	(3.509)	(1.678)	(7.424)	(4.057)	(2.165)
Daily volatility $(t-3)$	0.098***	0.088***	0.014	0.154***	0.093***	0.077*
	(7.463)	(4.803)	(0.473)	(10.901)	(5.813)	(1.989)
Intercept	1.367**	2.165***	1.587***	0.077	0.373	1.541*
	(2.446)	(11.491)	(3.158)	(0.245)	(0.812)	(1.900)
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	601,694	127,019	27,357	84,924	9,071	6,440
R^2	0.476	0.482	0.459	0.514	0.496	0.411

Table 3.8: ETF ownership and debt securities volatility

This table reports estimates from OLS regressions of daily debt securities volatility on ETF ownership and control variables. In the (All) column estimates using the entire sample are presented, and in subsequent columns estimates are presented for the largest countries individually. The dependent variable and ETF ownership are standardised. Standard errors are double-clustered at the country and month levels for column (All), and security and month levels for subsequent columns. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from January 2016 to December 2018.

Dependent Variable:	Daily volatility (t)					
	(All)	(US)	(UK)	(France)	(Netherlands)	(Germany)
ETF ownership ($t-1$)	−0.010**	−0.008*	−0.010	−0.019*	−0.004	−0.044
	(−2.411)	(−1.857)	(−0.697)	(−1.758)	(−0.377)	(−1.464)
Credit rating ($t-1$)	0.009	0.023*	−0.006	0.066	−0.020	−0.019
	(0.729)	(1.962)	(−0.180)	(1.269)	(−0.767)	(−0.792)
Time to maturity ($t-1$)	0.002	−0.000	0.129***	0.004***	−0.001***	0.000
	(0.113)	(−0.085)	(5.745)	(3.066)	(−3.218)	(0.000)
Bond zero ($t-1$)	−0.030	−0.040	−0.183*	−0.075	−0.041	1.642
	(−1.303)	(−1.006)	(−1.717)	(−0.511)	(−0.359)	(1.481)
Bid-ask spread ($t-1$)	3.224*	10.322**	29.906***	53.877***	3.891	89.145***
	(2.018)	(2.557)	(2.949)	(4.556)	(0.669)	(3.439)
Turnover ($t-1$)	0.005	−0.082	3.962	4.131	0.378	34.298***
	(0.358)	(−1.196)	(0.990)	(0.479)	(0.076)	(3.005)
Equity fund ownership ($t-1$)	−6.153**	−9.953	41.955***	−77.322***	16.056	−5.792
	(−2.106)	(−1.470)	(4.549)	(−3.338)	(0.863)	(−0.324)
Hedge fund ownership ($t-1$)	0.454	−3.802*	−0.578	84.710***	−8.056	5.060
	(0.195)	(−1.951)	(−0.108)	(3.183)	(−0.690)	(0.785)
MM fund ownership ($t-1$)	0.744*	1.050	0.677	0.668	0.509	6.528**
	(1.759)	(1.096)	(0.498)	(0.494)	(1.212)	(2.534)
Mixed fund ownership ($t-1$)	0.262	−0.082	−3.355*	−1.400	1.331	−2.892
	(0.576)	(−0.114)	(−1.734)	(−0.733)	(1.310)	(−0.356)
Bond fund ownership ($t-1$)	−0.116	−0.223	0.358	0.109	−0.113	0.035
	(−0.593)	(−0.729)	(0.630)	(0.097)	(−0.251)	(0.038)
Other fund ownership ($t-1$)	0.018	0.579	−1.262	−1.174	0.089	−3.108
	(0.016)	(0.372)	(−0.493)	(−0.384)	(0.028)	(−0.402)
Daily volatility ($t-1$)	0.214***	0.262***	0.075	0.219***	0.060	0.181
	(8.738)	(5.751)	(1.550)	(4.766)	(1.084)	(0.830)
Daily volatility ($t-2$)	0.073	0.144***	0.052	0.023	0.029	0.017
	(1.645)	(3.546)	(1.395)	(1.033)	(0.897)	(0.730)
Daily volatility ($t-3$)	0.065	0.129***	0.040	0.024	0.025	0.016
	(1.073)	(3.674)	(1.301)	(0.951)	(0.435)	(1.051)
Intercept	−0.100	−0.241**	−1.343***	−0.665	0.174	−1.832
	(−0.640)	(−2.330)	(−4.410)	(−1.669)	(0.660)	(−1.686)
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	513,292	244,729	41,948	33,161	29,464	14,549
R^2	0.501	0.590	0.466	0.633	0.301	0.655

underlying equities' returns than on the underlying debt securities' returns. Third, while higher ETF ownership increases equities' volatility, it decreases debt securities' volatility.

We argue that these effects are due to a strong information link formed between ETFs and equities but a much weaker one between ETFs and debt securities as well as due to different levels of arbitrage activity. The accessibility of equity markets fosters the formation of a strong information link and facilitates the exploitation of arbitrage opportunities. However, the hard-to-trade nature of the debt securities results in a weaker information link and inhibits arbitrage.

As a result, we document illiquidity contagion occurring between ETFs and equities but not between ETFs and debt securities, since a breakdown of the information link when ETFs become illiquid would affect equities more severely than debt securities. Similarly, the effect of ETF flows on equities' returns is much stronger than the one on debt securities' returns as equities are strongly affected by ETF demand shocks through arbitrage but debt securities are less so. Finally, equities' volatility increases due to increased arbitrage activity as ETF ownership increases, but debt securities' volatility decreases as investors satisfy their liquidity demand through the (more liquid) ETFs.

Our results indicate that ETFs can affect the underlying markets in different ways depending on their accessibility. From a policy perspective, this has important implications in understanding the extent to which ETFs can propagate shocks as well as their effects on different aspects of the underlying assets including their liquidity, prices and volatility. Future research should investigate more directly the role of market accessibility and arbitrageurs in driving the results presented in this paper, and examine the effects during a period of severe market stress when ETFs face large redemption shocks from authorised participants.

Appendix B

B.1 Variable Definitions

Table B.1: Variable Definitions

Variable	Description	Source
Panel A: Equities		
Daily stock volatility	Standard deviation of daily stock returns within a month.	Bloomberg
ETF ownership	The sum of positions held by ETFs in the stock at each quarter, divided by the stock's daily market capitalisation. We assume that positions remain constant throughout the quarter.	CBI data and Bloomberg
Equity/Hedge/MMF/ Mixed/Bond/Other/ RE fund ownership	The sum of positions held by ETFs of each fund type in the stock at each quarter, divided by the stock's daily market capitalisation. We assume that positions remain constant throughout the quarter.	CBI data and Bloomberg
Log(Market Cap)	The natural logarithm of the product of the stock's shares outstanding and daily price.	Bloomberg
1/Price	The inverse of the daily stock price.	Bloomberg
Amihud ratio	The average of the absolute stock daily return divided by the euro volume within a month.	Bloomberg
Bid-ask spread	The midpoint bid-ask spread.	Bloomberg
Book-to-market	Book value of assets / Market value of assets, where Market value of assets = Market capitalisation + Book value of debt.	Bloomberg
Past 12-month returns	The cumulative daily stock returns of the past 12 months.	Bloomberg
Gross profitability	(Revenue - Cost of goods sold) / Book value of assets, following Novy-Marx (2013).	Bloomberg
Security-level ETF flows	The stock-level weighted ETF flows divided by the stock's volume.	CBI data and Bloomberg
Security-level ETF bid-ask spread	The stock-level weighted ETF bid-ask spreads.	CBI data and Bloomberg
Security-level ETF mispricing	The stock-level weighted ETF mispricing.	CBI data and Bloomberg
Ret[y, x]	The cumulative stock return from date x to y.	Bloomberg
Order imbalance	(Ask % volume - Bid % volume) $\times$ Volume / Shares outstanding.	Bloomberg

Table B.1: Variable Definitions (continued)

Variable	Description	Source
Panel B: Debt securities		
Daily debt volatility	Standard deviation of daily debt security returns within a month.	Markit
ETF ownership	The sum of positions held by ETFs in the debt security at each quarter, divided by the security's amount outstanding. We assume that positions remain constant throughout the quarter.	CBI data
Equity/Hedge/MMF/ Mixed/Bond/Other/ RE fund ownership	The sum of positions held by ETFs of each fund type in the debt security at each quarter, divided by the security's amount outstanding. We assume that positions remain constant throughout the quarter.	CBI data
Credit rating	The debt security's credit rating in a scale of 1 (highest rating) to 22 (lowest rating) following Dimitrov et al. (2015).	CBI data
Time to maturity	The debt security's time to maturity in years.	Markit
Age	The debt security's age in years.	CBI data
Log(Amount outstanding)	The natural logarithm of the debt security's amount outstanding.	CBI data
Bond zero	The fraction of days in a month that the debt security did not trade.	Markit
Log(Trades)	The natural logarithm of the debt security's number of trades per month.	Markit
Amihud ratio	The average of the absolute debt security's daily return divided by the euro volume within a month.	Markit
Bid-ask spread	The midpoint bid-ask spread.	Markit
Turnover	The debt security's average daily volume over a month divided by the amount outstanding.	CBI data and Markit
Log(Average trade size)	The natural logarithm of the debt security's average daily volume over a month divided by the average number of trades over a month.	Markit
Security-level ETF flows	The debt security-level weighted ETF flows divided by the security's volume.	CBI data, Bloomberg and Markit
Security-level ETF bid-ask spread	The debt security-level weighted ETF bid-ask spreads.	CBI data, Bloomberg and Markit
Security-level ETF mispricing	The debt security-level weighted ETF mispricing.	CBI data, Bloomberg and Markit
Ret[y, x]	The cumulative debt security's return from date x to y.	Markit

B.2 Illiquidity contagion alternative thresholds

Table B.2: ETF bid-ask spreads and stock bid-ask spreads (70th percentile)

This table reports estimates from OLS regressions of daily stock bid-ask spreads on ETF bid-ask spreads and control variables. ETF bid-ask spreads are divided by market capitalisation and standardised. VIX and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 70th percentile. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from March 2014 to December 2018.

Dependent Variable:	Bid-ask spread (t)			
	(1)	(2)	(3)	(4)
ETF bid-ask spread ($t-1$) (%)	0.012***	0.017***	0.011**	0.017**
	(3.072)	(3.226)	(2.268)	(2.592)
ETF bid-ask spread (%) * VIX ($t-1$)		−0.009***		−0.009***
		(−3.049)		(−3.014)
ETF bid-ask spread (%) * ETF mispricing ($t-1$)			0.001	0.001
			(0.654)	(0.351)
log(MktCap ($t-1$))	−0.002***	−0.002***	−0.002***	−0.002***
	(−3.389)	(−3.393)	(−3.388)	(−3.392)
1/Price ($t-1$)	0.000	0.000	0.000	0.000
	(0.834)	(0.842)	(0.839)	(0.844)
Amihud ratio ($t-1$)	0.111***	0.111***	0.111***	0.111***
	(2.796)	(2.797)	(2.797)	(2.797)
Bid-ask spread ($t-1$)	0.576***	0.576***	0.576***	0.576***
	(15.478)	(15.466)	(15.478)	(15.466)
Book-to-market ($t-1$)	0.000***	0.000***	0.000***	0.000***
	(10.348)	(10.057)	(10.351)	(10.106)
Past 12-month returns ($t-1$)	0.000*	0.000*	0.000*	0.000*
	(1.830)	(1.833)	(1.827)	(1.829)
Gross profitability ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.418)	(−0.441)	(−0.416)	(−0.440)
Order imbalance ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.655)	(−0.656)	(−0.655)	(−0.657)
Ret[$t-1, t-2$]	0.000	0.000	0.000	0.000
	(0.352)	(0.355)	(0.352)	(0.355)
Intercept	0.018***	0.018***	0.018***	0.018***
	(3.712)	(3.717)	(3.711)	(3.716)
Day fixed effects	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes
Observations	11,411,458	11,411,458	11,411,458	11,411,458
R^2	0.566	0.566	0.566	0.566

Table B.3: ETF bid-ask spreads and stock bid-ask spreads (80th percentile)

This table reports estimates from OLS regressions of daily stock bid-ask spreads on ETF bid-ask spreads and control variables. ETF bid-ask spreads are divided by market capitalisation and standardised. VIX and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 80th percentile. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from March 2014 to December 2018.

Dependent Variable:	Bid-ask spread (t)			
	(1)	(2)	(3)	(4)
ETF bid-ask spread ($t-1$) (%)	0.012***	0.014***	0.009***	0.012***
	(3.072)	(3.438)	(2.659)	(3.007)
ETF bid-ask spread (%) * VIX ($t-1$)		−0.006***		−0.006***
		(−3.991)		(−3.792)
ETF bid-ask spread (%) * ETF mispricing ($t-1$)			0.004***	0.003***
			(3.321)	(2.873)
log(MktCap ($t-1$))	−0.002***	−0.002***	−0.002***	−0.002***
	(−3.389)	(−3.390)	(−3.387)	(−3.388)
1/Price ($t-1$)	0.000	0.000	0.000	0.000
	(0.834)	(0.842)	(0.839)	(0.846)
Amihud ratio ($t-1$)	0.111***	0.111***	0.111***	0.111***
	(2.796)	(2.797)	(2.797)	(2.797)
Bid-ask spread ($t-1$)	0.576***	0.576***	0.576***	0.576***
	(15.478)	(15.473)	(15.478)	(15.474)
Book-to-market ($t-1$)	0.000***	0.000***	0.000***	0.000***
	(10.348)	(9.777)	(10.351)	(8.801)
Past 12-month returns ($t-1$)	0.000*	0.000*	0.000*	0.000*
	(1.830)	(1.832)	(1.825)	(1.827)
Gross profitability ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.418)	(−0.434)	(−0.408)	(−0.425)
Order imbalance ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.655)	(−0.655)	(−0.656)	(−0.656)
Ret[$t-1, t-2$]	0.000	0.000	0.000	0.000
	(0.352)	(0.354)	(0.352)	(0.354)
Intercept	0.018***	0.018***	0.018***	0.018***
	(3.712)	(3.714)	(3.710)	(3.712)
Day fixed effects	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes
Observations	11,411,458	11,411,458	11,411,458	11,411,458
R^2	0.566	0.566	0.566	0.566

Table B.4: ETF bid-ask spreads and debt securities bid-ask spreads (70th percentile)

This table reports estimates from OLS regressions of daily debt securities bid-ask spreads on ETF bid-ask spreads and control variables. ETF bid-ask spreads are divided by market capitalisation and standardised. MOVE and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 70th percentile. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from January 2016 to December 2018.

Dependent Variable:	Bid-ask spread (t)			
	(1)	(2)	(3)	(4)
ETF bid-ask spread ($t-1$) (%)	−0.000	−0.000	−0.002	−0.002
	(−1.482)	(−1.594)	(−1.385)	(−1.409)
ETF bid-ask spread (%) * MOVE ($t-1$)		0.000		0.000
		(1.081)		(1.066)
ETF bid-ask spread (%) * ETF mispricing ($t-1$)			0.001	0.001
			(1.224)	(1.219)
Credit rating ($t-1$)	0.000***	0.000***	0.000***	0.000***
	(3.674)	(3.674)	(3.675)	(3.675)
Bid-ask spread ($t-1$)	0.954***	0.954***	0.954***	0.954***
	(57.249)	(57.249)	(57.249)	(57.249)
Time to maturity ($t-1$)	0.000	0.000	0.000	0.000
	(1.067)	(1.067)	(1.067)	(1.067)
Bond zero ($t-1$)	−0.000***	−0.000***	−0.000***	−0.000***
	(−3.044)	(−3.044)	(−3.045)	(−3.044)
Turnover ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.664)	(−0.714)	(−0.530)	(−0.580)
Ret[$t-1, t-2$]	−0.057**	−0.057**	−0.057**	−0.057**
	(−2.416)	(−2.416)	(−2.416)	(−2.416)
Intercept	−0.001	−0.001	−0.001	−0.001
	(−0.984)	(−0.984)	(−0.984)	(−0.984)
Day fixed effects	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes
Observations	11,698,589	11,698,589	11,698,589	11,698,589
R^2	0.961	0.961	0.961	0.961

Table B.5: ETF bid-ask spreads and debt securities bid-ask spreads (80th percentile)

This table reports estimates from OLS regressions of daily debt securities bid-ask spreads on ETF bid-ask spreads and control variables. ETF bid-ask spreads are divided by market capitalisation and standardised. MOVE and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 80th percentile. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from January 2016 to December 2018.

Dependent Variable:	Bid-ask spread (t)			
	(1)	(2)	(3)	(4)
ETF bid-ask spread $(t-1)$ (%)	−0.000	−0.000	−0.001	−0.001
	(−1.482)	(−1.562)	(−1.392)	(−1.424)
ETF bid-ask spread (%) * MOVE $(t-1)$		0.000		0.000
		(0.808)		(0.797)
ETF bid-ask spread (%) * ETF mispricing $(t-1)$			0.001	0.001
			(1.254)	(1.237)
Credit rating $(t-1)$	0.000***	0.000***	0.000***	0.000***
	(3.674)	(3.674)	(3.675)	(3.675)
Bid-ask spread $(t-1)$	0.954***	0.954***	0.954***	0.954***
	(57.249)	(57.249)	(57.249)	(57.249)
Time to maturity $(t-1)$	0.000	0.000	0.000	0.000
	(1.067)	(1.067)	(1.067)	(1.067)
Bond zero $(t-1)$	−0.000***	−0.000***	−0.000***	−0.000***
	(−3.044)	(−3.044)	(−3.045)	(−3.045)
Turnover $(t-1)$	−0.000	−0.000	−0.000	−0.000
	(−0.664)	(−0.694)	(−0.551)	(−0.581)
Ret$[t-1, t-2]$	−0.057**	−0.057**	−0.057**	−0.057**
	(−2.416)	(−2.416)	(−2.416)	(−2.416)
Intercept	−0.001	−0.001	−0.001	−0.001
	(−0.984)	(−0.984)	(−0.984)	(−0.984)
Day fixed effects	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes
Observations	11,698,589	11,698,589	11,698,589	11,698,589
R^2	0.961	0.961	0.961	0.961

B.3 Country-level ETF flows and security returns

Table B.6: ETF flows and country stock returns

This table reports estimates from OLS regressions of daily stock returns on ETF flows and control variables. ETF flows are divided by market capitalisation and standardised. Standard errors are double-clustered at the security and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from March 2014 to December 2018.

Dependent Variable:	Ret[$t, t-1$]				
	(US)	(UK)	(Japan)	(Germany)	(France)
ETF flows ($t-1$) (%)	0.002	0.007	0.002	0.000	0.040**
	(0.154)	(0.199)	(0.982)	(0.095)	(2.437)
log(MktCap ($t-1$))	−0.002***	−0.003***	−0.003***	−0.002***	−0.001***
	(−5.316)	(−9.027)	(−11.414)	(−6.904)	(−2.748)
1/Price ($t-1$)	0.000***	0.000**	−0.000	0.003	0.005***
	(3.226)	(2.020)	(−0.677)	(0.799)	(3.528)
Amihud ratio ($t-1$)	13.600	0.022	−917.714***	−9.423	−131.042
	(0.606)	(0.259)	(−2.721)	(−1.212)	(−0.690)
Bid-ask spread ($t-1$)	−0.005	−0.025**	0.030	−0.078***	−0.005
	(−0.975)	(−2.107)	(1.127)	(−4.174)	(−0.359)
Book-to-market ($t-1$)	−0.000	0.000	0.000***	0.000***	0.000
	(−1.426)	(0.797)	(2.588)	(3.664)	(0.798)
Past 12-month returns ($t-1$)	−0.000	0.000	0.000***	0.000**	0.000
	(−1.488)	(0.975)	(2.931)	(2.293)	(1.188)
Gross profitability ($t-1$)	0.002***	0.001***	0.004***	0.001	0.004**
	(2.805)	(2.909)	(6.162)	(0.581)	(2.394)
Order imbalance ($t-1$)	0.000	−0.001***	−0.000	0.005***	−0.001
	(1.107)	(−4.950)	(−0.605)	(6.472)	(−1.361)
Ret[$t-1, t-2$]	−0.020***	−0.012*	−0.006	−0.065***	0.013*
	(−3.186)	(−1.931)	(−1.475)	(−9.301)	(1.912)
Intercept	0.011***	0.019***	0.021***	0.018***	0.009**
	(5.372)	(8.699)	(10.999)	(6.470)	(2.278)
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	2,463,258	518,077	1,598,692	183,816	132,885
R^2	0.132	0.174	0.263	0.203	0.181

Table B.7: ETF flows and country debt securities returns

This table reports estimates from OLS regressions of daily debt securities returns on ETF flows and control variables. ETF flows are divided by market capitalisation and standardised. Standard errors are double-clustered at the security and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from January 2016 to December 2018.

Dependent Variable:	Ret$[t, t-1]$				
	(US)	(UK)	(France)	(Netherlands)	(Germany)
ETF flows $(t-1)$ (%)	0.002*	0.000	−0.000	0.000	−0.000
	(1.896)	(0.675)	(−0.022)	(0.647)	(−1.078)
Credit rating $(t-1)$	0.000	−0.000	0.000	0.000	0.000
	(0.413)	(−1.178)	(0.500)	(0.920)	(1.542)
Bid-ask spread $(t-1)$	0.008	0.127*	−0.001	−0.013*	−0.079*
	(1.321)	(1.799)	(−0.086)	(−1.708)	(−1.685)
Time to maturity $(t-1)$	0.000**	0.000***	−0.000***	−0.000***	0.000
	(2.493)	(5.988)	(−8.896)	(−3.497)	(0.000)
Bond zero $(t-1)$	−0.000***	−0.000**	−0.000	0.000	−0.000
	(−3.220)	(−2.300)	(−0.903)	(0.154)	(−0.258)
Turnover $(t-1)$	−0.000	−0.004	−0.015	−0.002	0.010
	(−0.431)	(−0.514)	(−1.582)	(−0.545)	(0.699)
Ret$[t-1, t-2]$	−0.085***	−0.041*	0.001	−0.006	0.000
	(−6.538)	(−1.930)	(0.331)	(−0.583)	(0.041)
Intercept	−0.000	−0.002***	0.000	−0.001	0.000
	(−0.430)	(−4.973)	(0.343)	(−0.823)	(0.448)
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	5,493,436	957,172	752,837	663,507	357,513
R^2	0.067	0.124	0.080	0.044	0.097

Chapter 4

Systemic Liquidity Risk and Money Market Funds

Abstract

This paper examines the ability of the liquidity coverage ratio (LCR) to protect the banks against systemic liquidity risk arising from their interconnectedness with money market funds (MMFs). I develop a network model of banks (sellers) and MMFs (buyers) of money market securities and simulate MMF redemptions which can trigger asset sales and a disruption to the funding of the banks. The model is calibrated to the full holdings data of the US prime MMFs as of the end of 2017 following the introduction of the post-crisis regulations aimed at mitigating runs on MMFs and the adoption of LCR. I find that the banks can withstand the MMF funding withdrawal without breaching their LCR regulatory requirements even in the face of extreme MMF redemption shocks. The post-crisis reforms have similarly made MMFs more capable to withstand large redemptions, although they can still face severe losses if their cash is depleted and the banks are unwilling to accommodate asset sales. The results indicate that LCR can be effective from a macroprudential perspective at mitigating systemic liquidity risk.

4.1 Introduction

The global financial crisis highlighted the importance of addressing systemic liquidity risk, defined as the simultaneous liquidity stress of multiple financial institutions (IMF, 2011). As the crisis deepened, many banks were unable to rollover or issue new short-term debt, which resulted in a reduction of credit provision to the real economy (Ivashina and Scharfstein (2010), Acharya and Mora (2015)). The systemic nature of liquidity risk manifested through the direct interconnectedness between borrowing banks and creditors who were prone to withdraw their funding under stress (e.g. money market funds - MMFs), as well as indirect interconnectedness through common asset holdings and fire sales externalities.

In response to these events, the post-crisis regulatory framework of Basel III mandated that banks need to hold enough high-quality liquid assets (HQLA) to withstand a funding shock for a stress period of 30 days through their liquidity coverage ratio (LCR). However, LCR is inherently microprudential in nature as it does not take into account the interconnectedness that exists between financial sectors (Bonner et al., 2018). As such, the question of whether it helps in mitigating systemic liquidity risk, a macroprudential concern, remains open and is the focus of this paper.

In this paper, I focus on a specific aspect of systemic liquidity risk, the direct interconnectedness that exists between banks and MMFs, which facilitate the short-term liquidity needs of financial institutions by investing in commercial paper, certificates of deposit and repurchase agreements (repos). At the peak of the financial crisis, the default of Lehman Brothers led US prime MMFs investing in corporate debt to experience investor redemption requests totalling $400 billion due to their liquidity mismatch as well as their perceived inability to maintain a constant share price of $1, forcing them to cut down lending in order to meet these requests and exacerbating the funding problems of the financial sector (IMF, 2010). While regulations were introduced to reduce MMFs' fragility following the financial crisis, they again experienced runs during the recent Covid-19 crisis due to investors' flight-to-quality and search for cash. Without regulatory intervention, the run could have triggered widespread contagion, propagating systemic liquidity risk

(Cunliffe (2020), BoE (2020a)).

To answer my research question, I develop a network model of MMFs and banks and assess whether redemptions incurred by the former can significantly impair the available liquidity of the latter. The redemptions can be modelled either exogenously (liquidity risk) or endogenously as a result of losses due to a bank default (i.e. a Lehman scenario - counterparty risk). To satisfy the redemptions, the MMFs stop reinvesting the proceeds from maturing securities which creates a funding shortfall for the banks. The banks then attempt to cover this shortfall in the overnight interbank market, which can create upward pressure on interbank rates, propagating liquidity stress. In extreme cases where MMFs have insufficient cash to satisfy redemptions, they resort to asset sales. Due to the absence of an active secondary market of money market securities, they ask the issuing banks to buy back the assets, and the latter can impose haircuts if they have insufficient liquidity, creating fire sales losses for MMFs and a new round of redemptions.

The network model by its nature facilitates the study of interactions between market participants due to direct interconnectedness and is ideal for assessing their resilience under stress. Importantly, the model incorporates the post-crisis US MMF regulations designed to strengthen their resilience and mitigate first-mover advantages to accurately capture the dynamics that can unfold during stress. To the best of my knowledge, this paper is the first attempt to model the liquidity stress propagation from MMFs to banks in the current regulatory environment and assess whether MMFs contribute to systemic liquidity risk. Furthermore, in order to test the effectiveness of the LCR regulation in isolation of the post-crisis MMF regulations, I run a counterfactual analysis assuming the latter have not been implemented. This allows me to assess whether the banks could withstand a funding shock originating from MMFs of similar magnitude as in the financial crisis assuming the LCR regulation was in place.

The model is calibrated to the security-level US prime MMF holdings data as of December 2017 which provide a detailed picture of the network of exposures between MMFs and the largest issuer banks of money market securities. This enables the identification of the important nodes in the network in spreading contagion and an accurate assessment of whether MMFs can propagate systemic liquidity risk to the banking sector. The holdings data are complemented by data on the banks' LCR and available HQLA as well as their positions in the overnight interbank market to measure their ability to withstand liquidity shocks.

My main finding is that LCR is effective at protecting the banking sector against systemic liquidity risk arising from the interconnectedness with the MMF sector as the banks are able to retain their regulatory LCR requirement of 100% even in the presence of very large MMF redemption shocks not observed historically. The liquidity buffers held by both banks and MMFs have increased their resilience, although when banks are unwilling to accommodate asset sales the resulting fire sales can create significant losses for the MMFs.

More specifically, when looking at the model results due to counterparty risk, i.e. due to bank defaults, I find that the MMF asset losses arising from their exposures to the defaulting banks reach up to $13.607 billion or 2.9% of total MMF assets. In most cases the MMFs are able to accommodate the redemptions that are generated as a result of the losses due to the banks' defaults using their available cash without resorting to asset sales, which only reach $24 million in the worst-case scenario. Because of this, the MMFs do not suffer fire sales losses and the secondary redemptions are negligible. The limited disruption to MMFs makes the banks suffer HQLA losses of up to $1.213 billion, or 1 basis point (bp) of total available HQLA, which they can comfortably accommodate without breaching the regulatory threshold of 100%.

Next, I impose large exogenous redemption shocks on the MMFs to test their resilience against redemptions exceeding historical patterns (liquidity risk). In the most extreme scenario MMFs suffer asset losses of $164.579 billion or 34.9% of total MMF assets due to redemptions, which forces them to sell large amounts of assets of up to $69.626 billion to generate enough cash to satisfy them. The banks, faced with a large funding shortfall as MMFs stop reinvesting in them and the magnitude of assets they are asked to buy back, hoard liquidity and impose steep haircuts of 85% on average on these purchases while at the same time restricting lending in the interbank market. Interestingly, the results suggest that while MMFs' losses are not significantly negatively correlated with their liquidity buffers, they are strongly positively correlated with banks' haircuts and the absence of market liquidity. The negative returns create further losses for MMFs of up to \$4.271 billion due to secondary redemptions which forces the banks to utilise their HQLA reserves to cover the funding shortfall. Nonetheless, the total HQLA losses in this stress scenario reach up to \$64.964 billion, or 0.5% of total HQLA, which are still not sufficient to make any bank breach its regulatory threshold.

Finally, when considering the configuration without the post-crisis MMF regulations and a prime MMF sector similar in size before their implementation, the model results indicate that bank defaults can have a severe effect on MMFs due to their structural vulnerabilities that make investors prone to run. Specifically, the asset losses reach \$450.447 billion in the most extreme case or 27.8% of total MMF assets, which is similar to what was observed during the financial crisis. The resulting asset sales reach \$160.449 billion, which makes the banks impose haircuts averaging 52%, creating further losses for the MMFs. The total HQLA losses in this stress scenario reach \$169.493 billion or 1.4% of total HQLA, which while significant are still not sufficient to make any bank breach its regulatory threshold. This suggests that the introduction of LCR has made the banks resilient to liquidity shocks originating from MMFs similar in magnitude as was observed during the financial crisis.

Against the backdrop of the ongoing Covid-19 crisis, my paper has several policy implications. First, the LCR requirement helps banks to mitigate systemic liquidity risk arising from the interconnectedness with the MMF sector, independently of the post-crisis MMF reforms. As such, they are able to withstand severe liquidity shocks in money markets without significantly impairing their ability to function during times of stress. Second, while the MMF reforms have increased their capacity to satisfy redemptions, my results indicate that in the absence of a buyer of last resort the MMFs can still incur severe losses when large redemption shocks occur and the banks are unwilling to accommodate asset sales. Hence, future reforms should focus on improving the market liquidity of money market instruments rather than further increasing MMFs' liquidity buffers.

My paper contributes to several strands of literature. On systemic liquidity risk, Farhi and Tirole (2012) show theoretically that without macroprudential regulation, banks choose to hold sub-optimal liquidity buffers and rely on government bailouts during a crisis. Several empirical papers have focused on the events of the financial crisis. Gorton and Metrick (2012) describe the propagation of systemic liquidity risk through indirect interconnectedness that occurred during the financial crisis as a result of the run on the repo market. Ashcraft et al. (2011) find that US banks that acted as sponsors to asset-backed commercial paper (ABCP) conduits and were subject to liquidity shocks in the summer of 2007 hoarded liquidity, increasing rates in the interbank market. Similarly, Acharya and Merrouche (2013) document liquidity hoarding in the UK interbank market in the summer of 2007 and find an increase in the borrowing rates of all UK banks irrespectively of their counterparty risk. Finally, Ivashina and Scharfstein (2010), Cornett et al. (2011) and Acharya and Mora (2015) show that banks reduced credit provision to the real economy as a result of the liquidity crunch.

Fewer papers have focused on the effects of the post-crisis LCR regulation on the mitigation of systemic liquidity risk. Among them, Aldasoro and Faia (2016) and Ferrara et al. (2019) document that skewing the distribution of liquid assets towards systemic banks in the interbank network minimises systemic liquidity risk. My paper contributes by looking at the propagation of systemic liquidity risk across multiple financial sectors, MMFs and banks, in order to provide a more holistic view of the contagion mechanism and assess whether stress similar to the crisis period can have equally detrimental effects to the banks post-crisis.

My paper also contributes to the literature on MMFs. The empirical strand has extensively analysed the crisis period. Kacperczyk and Schnabl (2013) find that MMF managers had strong incentives to increase the riskiness of their portfolios before the crisis in order to attract inflows, but once the shocks materialised the riskier MMFs also experienced larger outflows. Chernenko and Sunderam (2014) investigate the European debt crisis in 2011 and find that MMFs that had large exposures to European banks suffered large outflows, which negatively affected corporates that relied on them for financing. Strahan and Tanyeri (2015) find that the MMFs that suffered large outflows following the collapse of Lehman Brothers sold their most liquid assets first to satisfy the redemptions due to the absence of an active secondary market for commercial paper. Schmidt et al. (2016) construct a simple model of strategic complementarities and find that institutional investors were more prone to run than retail investors because of information asymmetries. Gallagher et al. (2020) document the aversion of MMFs to hold assets that were exposed to negative news during the Eurozone crisis to avoid redemptions from sophisticated investors. Importantly, there has been scant empirical work looking at the post-crisis period and the stability of the MMF sector following the introduction of the new regulations. This paper contributes to fill this gap.[1]

The rest of the paper is structured as follows. Section 4.2 describes the institutional details of MMFs, section 4.3 presents the model, section 4.4 describes the data used in this study, section 4.5 analyses the results and section 4.6 concludes.

4.2 Institutional details

MMFs are open-ended investment vehicles that invest in high-quality short-term debt securities, both sovereign and corporate. As a result, they are considered low-risk vehicles that offer yields slightly higher than bank deposits since they are not covered by deposit insurance. US MMFs are categorised according to their clientele (retail vs. institutional funds) and their portfolio composition (government vs. prime funds). Retail MMFs cater to small investors while institutional MMFs serve large corporations and governments. Government MMFs invest in safe liquid government debt while prime MMFs invest mainly in riskier and higher-yield short-term corporate debt.

Prior to the financial crisis, most MMFs offered a constant net asset value (CNAV) of $1 (called the market NAV) as long as the true ("shadow") NAV did not deviate more than 50 bps, i.e. did not move below $0.995 or above $1.005. This fact, along with most MMFs having implicit support from their sponsors should they break the buck (i.e. lower their

[1] The theoretical strand of the MMF literature has focused on the efficiency of the new regulations in preventing runs. Cipriani et al. (2014) show that by introducing the possibility of a liquidity fee investors may be incentivised to run pre-emptively before it is actually implemented, a distortion that would not be present in the absence of such a measure. There is empirical evidence to support this prediction in the recent run on MMFs during the Covid-19 crisis (Li et al., 2020). In contrast, Lenkey and Song (2016) argue that the liquidity fee may increase or decrease the incentives of investors to run pre-emptively; on the one hand first-movers may avoid the fee but on the other any investors who stay benefit from a wealth transfer due to the fees imposed on the redeemers. Parlatore (2016) tests the efficiency of the new regulations in a general equilibrium setting and finds that the MMF industry is more stable without allowing sponsor support as mandated by EU regulation.

market NAV below $1), made MMFs appear as safe investments with capital losses almost impossible. However, when a large MMF, Reserve Primary Fund (RPF), broke the buck due to the default of Lehman Brothers, this perception abruptly changed. The result was a run on prime MMFs resulting in outflows totalling $400 billion (Schmidt et al., 2016), which abated only after the intervention of the US Treasury.

The run was a result of the opacity of the MMFs' holdings which increased the uncertainty of the investors about the true value of their investments. In addition, there were two important reasons why, once instigated, the run extended to multiple MMFs. First, CNAV MMFs are prone to runs due to first-mover advantage. The RPF investors who were quick enough to redeem their shares first were paid back the full price of $1 per share even though the shadow NAV had already dropped below that value. All remaining investors were forced to face losses which were exacerbated by the early redeemers withdrawing their funds at par. Second, even though most prime MMF securities are short-term in nature, most are inherently illiquid, making MMFs vulnerable to runs in a similar manner as the one described by Diamond and Dybvig (1983) for banks and Chen et al. (2010) more generally for mutual funds due to liquidity mismatch. Hence, an MMF is forced to use its most liquid assets first in order to repay early redeemers at full price, while remaining investors are left with highly illiquid securities which can only be sold at fire sales prices. In both cases, redeeming investors impose a negative externality on investors who do not redeem, which incentivises everyone to front-run others.

Because of these facts, the post-crisis regulations in the US mandate that prime institutional MMFs, which suffered the largest redemptions due to investor sophistication, adopt a variable net asset value (VNAV) that is marked-to-market. This conversion removes the incentive to redeem early since capital losses are automatically incorporated into the share price. Prime retail MMFs retain a constant NAV of $1 since the run risk is deemed to be small. Furthermore, in order to address the second cause of runs, securities illiquidity, both prime retail and prime institutional MMFs can impose a liquidity fee capped at 2% of redemption value if the weekly liquid assets (WLA)[2] fall below 30% of total assets. Further,

[2] The new regulations categorise MMF assets according to their liquidity into the following types. Daily liquid assets (DLA) include cash, US government debt and securities that mature within one business day. Weekly liquid assets (WLA) include cash, US government debt and securities that mature within five

if WLA fall below 10% of total assets, the fund managers would be obligated to impose a liquidity fee of 1% unless this is deemed to be against the best interest of the fund (SEC, 2014). This creates a transfer of value from the redeeming investors to the ones that stay in the fund, which compensates them for any potential losses due to fire sales, reducing the incentive to run. Sponsor support in the form of asset purchases above market value or direct cash injections remains, but the MMF must disclose it when this happens. Most US MMF sponsors are either banks or investment fund families. However, this support is not guaranteed and is at the discretion of the sponsor.

In Figure 4.1 I plot the evolution of US prime and government MMFs' total net assets (TNA) from 2000 to May 2020. As can be seen, while historically prime MMFs attracted more investment than government MMFs, the introduction of the new regulations in 2016 was preceded by a shift of $1 trillion from the former to the latter. This shows the strong preference of MMF investors for a stable NAV and capital preservation against small market fluctuations. The gap between prime and government MMFs widened further during the Covid-19 crisis as investors withdrew cash from the former and deposited it to the latter. As a result, prime MMFs had TNA of $715 billion while government MMFs had TNA of $3.9 trillion as of May 2020.

4.3 Model

4.3.1 Model overview

Consider a universe of banks and MMFs connected via funding linkages. In line with the current regulations, prime institutional MMFs are VNAV while prime retail MMFs are CNAV but both may impose a liquidity fee of up to 2% of redemptions should their WLA fall below 30% of total assets.

MMFs are linked to banks via ownership of debt securities (funding channel) and if they are bank-sponsored CNAV they are also beneficiaries of discretionary support in case of stress (sponsor channel). Both channels pose a risk to the banks which may see their

business days. Illiquid assets are assets that cannot be sold within seven days at market value.

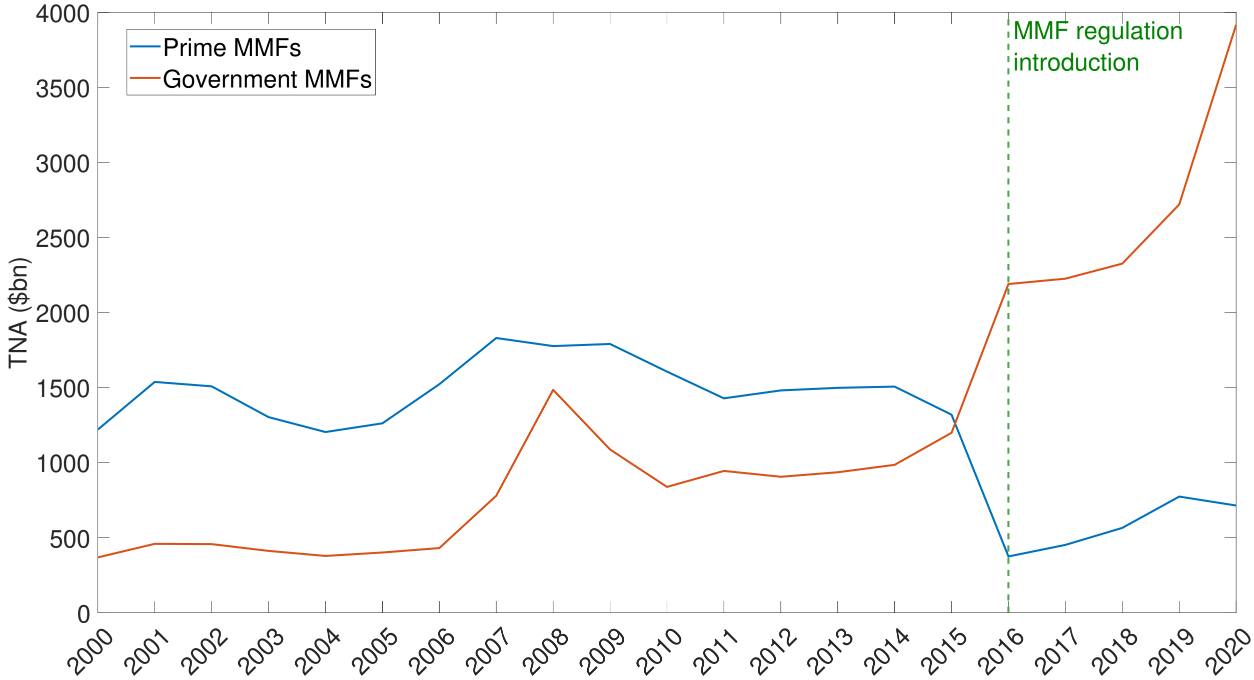

Figure 4.1: US prime and government MMFs' total net assets (TNA)

Source: iMoneyNet data and Investment Company Institute (ICI) statistics

funding dry up (rollover risk) while at the same time be forced to provide liquidity to their stressed funds. Furthermore, the banks are connected to each other via the unsecured overnight interbank market.

My model takes place over a period of a week, i.e. five business days to coincide with the available data on DLA and WLA and the typical timeframe before the introduction of regulatory support. On day 1, the MMFs experience a redemption shock that can be exogenous or a result of another shock (i.e. a bank default). Every day, the MMFs have an amount of liquidity available to meet redemptions. This amount comprises of cash, US Treasury debt which I assume to be perfectly liquid, and the securities which mature on that day and are converted to cash.

In line with the findings of Strahan and Tanyeri (2015), I assume that MMFs attempt to meet redemptions by first using their available cash instead of selling assets in a pro-rata fashion. This assumption is based on the fact that short-term corporate debt, with the exception of certificates of deposit (CDs), is not actively traded on a secondary market. Instead, if MMFs are forced to liquidate securities like commercial paper, they can only do so by asking the issuer to buy them back (Van Horne and Wachowicz, 2008). In order to be compliant with regulations, MMFs are assumed to use available cash only to the extent that their WLA do not drop below 30% and their DLA do not become lower than 10%. If this cash is not enough to cover redemptions, I assume that they further sell securities that are not DLA, WLA or illiquid and are issued by the banks in my sample. The banks can then decide to impose a haircut on the value of the securities they are asked to buy back, which creates further losses for the MMFs due to fire sales.[3] If the haircut is large enough such that the MMFs cannot satisfy the redemptions after the asset sale, they are forced to use their remaining cash reserves. However, since this can reduce their WLA below 30%, they can impose a liquidity fee of up to 2% of redemptions in order to protect their liquidity reserves. Throughout this exercise, I assume that MMFs experiencing redemptions stop buying new bank debt and keep cash reserves instead.

As a reaction to the drop in the supply of liquidity from MMFs, the banks attempt to cover the shortfall in the interbank market and at the same time decide the haircut to be imposed on the securities they are asked to buy back.[4] Banks that are sponsors also provide liquidity to the CNAV MMFs in danger of breaking the buck. The interbank market is modelled as a collection of risk-averse banks that act as profit maximisers and are constrained by their LCR requirements. The equilibrium interbank rate is a function of the banks' willingness to lend and the increase in interbank borrowing due to the withdrawal of MMF funding.

Finally, the MMFs calculate daily losses as a result of the redemptions. If there are no fire sales, VNAV MMFs suffer no losses since their NAV is marked-to-market. However, CNAV MMFs suffer losses if their shadow NAV is less than $1 since investors can redeem at par. If there are fire sales, both VNAV and CNAV MMFs experience losses, creating

[3] In reality, there exists an active secondary market for CDs so MMFs would not be constrained in selling them only to the issuer. However, since the identity of the specialised dealers that trade them is not publicly known, I treat them like all other securities and assume that only the issuer can buy them back.

[4] The haircut imposed is a function of the banks' available liquidity. Duygan-Bump et al. (2013) describe how market liquidity for commercial paper evaporated after Lehman's default due to pressure on the dealers' own capital and liquidity, which impaired the MMFs' ability to satisfy redemptions. Essentially, the dealers imposed large haircuts on the securities they were asked to buy back so the MMFs faced further losses. Several euro area MMFs were forced to ask issuing banks to buy back assets during the recent Covid-19 crisis as well according to the European Systemic Risk Board (ESRB) (ESRB, 2020).

further redemptions the next day according to a flow-performance relationship and the cycle repeats. The simulation ends after five days/rounds.

4.3.2 Model breakdown

4.3.2.1 Preliminary step: Initial shock

Consider a population of n_B banks and n_F MMFs belonging in the sets $N_B = \{1, 2, ..., n_B\}$ and $N_F = \{1, 2, ..., n_F\}$ respectively. Each day, the MMFs have available liquidity $C_{i,t}$ which is equal to their cash, US Treasury debt and the value of the securities maturing on the day. I start the stress testing exercise by imposing a redemption shock $S_{i,0},\ i \in N_F$ on the MMFs. This redemption shock can arise from two distinct sources and I present results for each one.

In the first stress scenario, I model a credit event akin to the default of Lehman Brothers by letting each bank default on its debt, which creates losses for the MMFs and subsequent redemptions. In this way I can measure the systemicness of each bank on the network by calculating the total losses originating due to its default, as well as the vulnerability of each MMF to each bank due to counterparty risk. I assume that the recovery rate of all uncollateralised bank debt is 40% so MMFs are faced with a loss-given-default of $\lambda = 0.6$ for each dollar of defaulted debt held. Collateralised securities such as ABCP and repos are assumed to preserve 100% of their value.[5] At this stage, non-defaulted banks that are sponsors must consider extending liquidity to MMFs under stress. It is assumed that banks always do so in order to avoid the reputational risk associated with not providing support as was observed during the financial crisis (BCBS, 2015). The banks will only support a prime retail MMF that has broken the buck and will supply enough liquidity to make its shadow NAV equal to \$0.995 (such that its market NAV is \$1). As a result, initial redemptions for supported funds will be zero. The initial return is calculated as the

[5]The results are qualitatively similar assuming 0% recovery rate of uncollateralised debt and 80% recovery rate of collateralised debt.

percentage change in market NAV:

$$return_{i,0} = \frac{MNAV_{i,1} - MNAV_{i,0}}{MNAV_{i,0}} \; \forall \; i \in N_F \tag{4.3.1}$$

where $MNAV_{i,0}$ is the market NAV of MMF i at time 0 while $MNAV_{i,1}$ is the market NAV following the assets' devaluation due to the bank's default and any support received, if any.

The negative return is assumed to cause investors to withdraw their capital according to a flow-performance relationship that is estimated as follows:

$$Flow_{i,t+1} = \alpha + (\beta + u_i)Return_{i,t} + \gamma X_{i,t} + \epsilon_{i,t+1} \tag{4.3.2}$$

where $Flow_{i,t+1}$ is the percentage change in TNA of MMF i from month t to month $t+1$, $Return_{i,t}$ is the gross return of MMF i from month $t-1$ to month t, and, following Kacperczyk and Schnabl (2013), $X_{i,t}$ is a matrix of control variables including the logarithm of MMF size, the MMF's expense ratio, the MMF's age and the logarithm of the fund family size. In this study I use gross returns instead of yields because they take into account capital gains and losses, similarly to Witmer (2016). Since I use fund-level data, I aggregate the share class-level variables by using weighted averages according to each class's TNA.

For the purposes of the analysis, we are more interested in the individual MMF flow-performance relationships rather than an aggregate estimate which would allow us to capture the heterogeneity that exists among MMFs. For these reasons, and in order to preserve the panel nature of the data, I estimate the regression using a mixed effects model which incorporates a fixed effect common across all MMFs β as well as random effects unique for each MMF u_i. Finally, since institutional investors are more sensitive to past returns than retail ones, I estimate the regression separately for retail and institutional MMFs.

The endogenous MMF redemptions are thus:

$$S_{i,0} = (\beta + u_i)return_{i,0} \tag{4.3.3}$$

In the second stress scenario, I impose exogenous redemption shocks of various magnitudes to measure liquidity risk and assess the ability of MMFs to honour redemptions using available resources. This scenario reflects the events of the recent Covid-19 crisis where investors redeemed their capital due to flight-to-quality and search for cash rather than due to capital losses arising from a bank's default. By imposing arbitrary redemption shocks I can assess whether there exist plausible levels of stress not observed historically which could make MMFs propagate systemic liquidity risk.[6]

The redemptions from the two stress scenarios are used to update the MMFs' NAV as discussed next.

4.3.2.2 First step: Initial MMF losses

As a result of the redemptions, the MMFs' TNA, number of shares and shadow net asset value (SNAV) are updated as follows:

$$TNA_{i,t} = \begin{cases} TNA_{i,t-1} * (1 - S_{i,t-1}) \text{ if } i \in N_F \text{ is institutional or retail that broke the buck} \\ TNA_{i,t-1} - shares_{i,t-1} * S_{i,t-1} \text{ if } i \in N_F \text{ is retail that didn't breat the buck} \end{cases} \tag{4.3.4}$$

$$shares_{i,t} = shares_{i,t-1} * (1 - S_{i,t-1}) \tag{4.3.5}$$

$$SNAV_{i,t} = \frac{TNA_{i,t}}{shares_{i,t}} \tag{4.3.6}$$

Prime institutional MMFs suffer no losses to their shadow NAV since the numerator and the denominator are reduced by the same amount. This follows from the fact that they mark-to-market their NAV. On the other hand, prime retail MMFs that haven't broken the buck can have a reduction of TNA that is greater than the reduction of their shares since they are obligated to pay $1 for each redeeming share. As a result, their shadow NAV will be reduced if it was less than $1 prior to the shock. However, if they have broken the buck

[6] In unreported results, I also considered redemptions as a result of losses due to an increase of interest rates. The findings suggest that MMFs can withstand losses arising from extreme rate shocks of 300 bps without facing significant redemptions due to the short maturity profile of their investments.

I assume that they pay redeemers at market values. In reality, a retail MMF that cannot preserve a share price of $1 is likely to face large redemption requests and as a result suspend redemptions in order to manage an orderly liquidation of its assets as happened with RPF. I abstract from such complexities in the baseline model by assuming that in such cases MMFs move to a VNAV format which limits their subsequent redemptions (as would happen if they were suspended).[7]

MMFs use their liquidity $C_{i,t}$ in order to satisfy the redemptions as long as their WLA remain above 30% and their DLA above 10% of $TNA_{i,t}$. If they do not have enough liquidity to do so without breaching those limits, they sell securities in order to generate enough cash to pay back investors. I randomise the sale procedure by letting MMFs sell securities that are not DLA, WLA or illiquid and are issued by the banks belonging in N_B. In the credit stress scenario, it is assumed that the defaulted bank does not accept asset sales and its securities become illiquid. Each MMF randomly selects securities until their total value is at least as high as the residual amount needed to satisfy all redemptions, after taking into account the available liquidity used first. Implicitly, by only considering the issuers in the subset N_B, I make the assumption that non-financial companies are not able to accommodate asset sales. This is reasonable to assume as most non-financial companies sell debt through dealers, who can buy it back when requested to do so.

4.3.2.3 Second step: Bank reaction

I assume that MMFs experiencing redemptions stop reinvesting the proceeds from the maturing securities. As a result, the banks are faced with rollover risk and need to cover the funding shortfall through the interbank market. The funding shortfall is calculated as follows:

$$FS_{i,t} = \sum_{z \in Z} maturing\ security_{i,j,z,t}\ \forall\ i \in N_B \text{ and } j \in J \tag{4.3.7}$$

where $FS_{i,t}$ is the funding shortfall of bank i on day t, and $maturing\ security_{i,j,z,t}$ is the value of security z belonging in the set Z of securities maturing on day t, issued by bank i,

[7] In section 4.5.3 I consider results from an alternative model configuration where institutional investors withdraw all their capital from CNAV MMFs that broke the buck.

and held by MMF j belonging in the set J of MMFs experiencing redemptions on that day.

The updated interbank liabilities are:

$$IL_{i,t} = IL_{i,t-1} + FS_{i,t} \tag{4.3.8}$$

where $IL_{i,t}$ are the interbank liabilities of bank i on day t.

If the bank is a sponsor, it also provides support to its funds as discussed in the previous section. The total support provided by a sponsor bank, if any, is:

$$Support_{i,t} = \sum_{j \in D} (0.995 - SNAV_{j,t}) * shares_{j,t} \text{ if } i \in N_B \text{ is sponsor} \tag{4.3.9}$$

where $Support_{i,t}$ is the total support in liquidity provided by bank i if it is a sponsor bank to the MMF j belonging in the set D of prime retail MMFs that have broken the buck (i.e. $SNAV_{j,t}$ lower than \$0.995). VNAV MMFs are not entitled to sponsor support since by definition they cannot break the buck.

Finally, the banks must consider the amount of securities they are willing to buy back from distressed MMFs. They can impose a haircut $f_{i,t} \in [0,1]$ which is applied uniformly on the value of the assets they are asked to buy, $Assets_{i,t}$, and is determined in equilibrium depending on their available liquidity.[8] Since the banks are the issuers of the debt they are asked to buy back, the repurchased securities expire and the banks are not required to hold capital for these positions. This is a key distinction with other dealer models where broker-dealers typically finance asset purchases with repo transactions and take into account the capital costs associated with warehousing assets (e.g. Baranova et al. (2017)).

I model the interbank market by using a modified version of the framework developed by Hałaj and Kok (2015). Each bank has a default probability which is simply estimated following Hull (2018) as:

$$p_{i,t} = \frac{s_{i,t}}{\lambda} \tag{4.3.10}$$

where $p_{i,t}$ is the default probability of bank i, $s_{i,t}$ is the CDS spread of i at time t and λ is

[8] I do not observe MMFs that own sponsor bank securities, hence a haircut does not negatively affect a bank's sponsored MMFs.

the loss-given-default parameter equal to 0.6.

Each bank is charged a risk premium $r^p_{i,t}$ over the risk-free rate r^f_t. This premium is calculated using the fact that, in expectation, the rate of return of lending to bank i must be equal to the risk-free rate:

$$r^f_t = (1 - p_{i,t})(r^f_t + r^p_{i,t}) + p_{i,t}(1 - \lambda)(r^f_t + r^p_{i,t}) \tag{4.3.11}$$

From this equation we derive:

$$r^p_{i,t} = \frac{p_{i,t}\lambda}{1 - p_{i,t}\lambda} r^f_t = \frac{s_{i,t}}{1 - s_{i,t}} r^f_t \tag{4.3.12}$$

I model the demand (liabilities) and supply (assets) channels separately. The overnight interbank market under consideration is assumed to be an over-the-counter market where banks allocate funds to each other according to a probability map P. This is a $n_B \times n_B$ matrix where the element P_{ij} denotes the probability of bank i having a lending relationship with bank j. I calibrate this matrix by using country-level data of interbank fund flows using the Bank for International Settlements (BIS) locational statistics.[9] Specifically, the probability of bank i residing in country A lending to bank j residing in country B is estimated as the fraction of funds lent by banks in country A to banks in country B to the total funds lent by banks in country A. Banks residing within the same country are assumed to lend to each other with probability 1.

After updating their interbank liabilities, the banks need to decide how to allocate them across the other banks. They do so by minimising their rollover risk, i.e. the risk that the lending bank will default and will not be able to rollover the loan. This risk is calculated by estimating the covariance matrix of the default probabilities $p_{i,t}$'s C, following Hałaj and Kok (2015). Let L^t denote the $n_B \times n_B$ matrix of interbank liabilities, where the element L^t_{ji} denotes the amount borrowed by bank i from bank j on day t. Each bank asks for funding from its peers by solving the following optimisation problem:

$$\min_{L^t_{ji}} \left[L^t_{1i} ... L^t_{n_B i} \right]^{\mathrm{T}} C \left[L^t_{1i} ... L^t_{n_B i} \right] \tag{4.3.13}$$

[9] `https://www.bis.org/statistics/bankstats.htm`

subject to:

$$\sum_j L^t_{ji} = IL_{i,t}$$

$$L^t_{ji} = 0 \text{ if } P_{ji} = 0$$

$$LCR_{i,t} = \frac{HQLA_{i,t} - IL_{i,t}(r^f_t + r^p_{i,t})}{stress_i} \geq 100\%$$

Each bank chooses the vector of L^t_{ij}'s that minimises its rollover risk, subject to the following conditions: first, the sum of the vector elements is equal to the total interbank liabilities; second, the bank asks for funding from bank j with probability P_{ij}; and third, the interest payment of the liabilities must not lower the bank's LCR below 100%, where $HQLA_{i,t}$ are the bank's available HQLA on day t and $stress_i$ are the bank's projected stress outflows over a 30-day period as provided in the annual report. The LCR in this optimisation is only a forecast based on the current market conditions as the market hasn't cleared. The final LCR is calculated when I model the supply side.

Once the banks have stated their requested amounts from their counterparts, the latter must decide whether they will extend the funding. The lending banks[10] act as risk-averse profit maximisers by considering the trade-off between the return on the amount lent and the riskiness of these returns. The riskiness is computed by estimating the volatility of the individual risk premia $r^p_{i,t}$, $\sigma = [\sigma_1, ..., \sigma_{n_B}]$, and their associated correlation matrix Q, which measures the correlation of the banks' default risk and comovement of reference rates that determine the cost of interbank funding. Let A^t denote the $n_B \times n_B$ matrix of interbank assets, where the element A^t_{ij} denotes the amount lent by bank i to bank j on day t. Each bank allocates resources in the interbank market by maximising the following risk-adjusted return:

$$\max_{A^t_{ij}, f_{i,t}} \Big[\sum_j A^t_{ij}(r^f_t + r^p_{j,t}) - (\sigma \circ A^t_{i\cdot}) Q (\sigma \circ A^t_{i\cdot})^{\mathrm{T}} \Big] \tag{4.3.14}$$

[10]Note that most banks act as borrowers and lenders simultaneously.

subject to:

$$0 \leq A_{ij}^t \leq L_{ij}^t$$

$$LCR_{i,t} = \frac{HQLA_{i,t} + \sum_j A_{ij}^t(r_t^f + r_{j,t}^p) - IL_{i,t}(r_t^f + r_{i,t}^p) - Support_{i,t} - (1 - f_{i,t})Assets_{i,t}}{stress_i} \geq \Lambda$$

where $\circ$ denotes the Hadamard product of element-by-element multiplication of the vectors σ and $A_{i\cdot}^t$.

The first condition states that the banks cannot lend more than what the borrowers requested. They can, however, lend less if they deem that the return is not adequate for the risk taken.

The second condition is the bank's LCR which must be higher than a lower threshold Λ. Each day, the banks' HQLA increase by the interest received on the interbank assets and decrease by the interest paid on the interbank liabilities. The HQLA are further reduced if a bank has to support an MMF, and if it decides to buy back the assets sold by the distressed MMFs. The bank has the option of applying a haircut $f_{i,t}$ to the value of the assets bought up to a maximum of 100% whereby it refuses to buy back entirely. The closer the bank is to breaching the lower LCR threshold Λ, the higher the haircut that it applies. In the simulations, I vary the value of Λ in order to capture liquidity hoarding. A high value indicates that banks prefer to hoard liquidity instead of lending it out and accommodating asset sales, which has negative repercussions for the other market participants.

If the banks do not lend the full amounts requested, the market does not clear at the current equilibrium rate r_t^f. I solve for the competitive equilibrium using a tâtonnement process by employing the exponential search algorithm described by Meisser and Kreuser (2017). The competitive equilibrium is defined as the interest rate r_t^f for which demand equals supply (market clears) and banks maximise their risk-adjusted return subject to the conditions stated in (4.3.14). As in all numerical solutions, I can only achieve an approximate solution within a tolerance level. In the simulations, equilibrium is achieved with a maximum deviation of 0.0001% between total interbank assets and liabilities.

In summary, as MMF redemptions get higher and liquidity to the banks is disrupted, their interbank liabilities increase and the equilibrium rate gets higher in order for supply to satisfy the increased demand.

4.3.2.4 Third step: MMF reaction

After the banks have imposed their haircuts $f_{i,t}$, the MMFs use the cash raised from the asset sales to satisfy residual redemptions. If the haircuts are such that the MMFs breach their WLA lower bound of 30% of $TNA_{i,t}$, they impose a liquidity fee on redemptions in order to retain their WLA lower bound, up to a maximum of 2%. The liquidity fee is calculated as follows:

$$fee_{i,t} = \begin{cases} \min\left(\frac{(0.3-WLA_{i,t})TNA_{i,t}}{0.7S_{i,t-1}TNA_{i,t-1}},\ 2\%\right) \text{ if } WLA_{i,t} < 30\% \\ 0 \ \text{ otherwise} \end{cases} \tag{4.3.15}$$

where $WLA_{i,t}$ are the updated WLA as a percentage of $TNA_{i,t}$ after taking into account the haircuts.

Finally, the MMFs calculate their final $TNA_{i,t}$ after taking into account haircuts and liquidity fees. They also update their $NAV_{i,t}$ and calculate their daily return as the percentage change in market NAV:

$$return_{i,t} = \frac{MNAV_{i,t} - MNAV_{i,t-1}}{MNAV_{i,t-1}} \ \forall\, i \in N_F \tag{4.3.16}$$

Following that, I calculate the new MMF redemptions:

$$S_{i,t} = (\beta + u_i)return_{i,t} \tag{4.3.17}$$

The new redemptions start the next round/day of the model since they force MMFs to use their new cash and sell assets in order to satisfy them.

4.3.3 Model implications

The model has several implications for the determinants of the propagation of systemic liquidity risk. First, it is a function of MMFs' TNA because as they increase in size and the banks rely more on them, the resulting funding shortfall can also become higher, depleting their available liquidity. Second, it is a function of the MMFs' DLA and WLA since higher cash reserves make them more able to satisfy redemptions without resorting to asset sales and potential losses. Third, it is a function of banks' available HQLA buffers which they can utilise to cover the funding shortfall and lend in the interbank market without impairing the provision of liquidity. Fourth, it is a function of banks' propensity to hoard liquidity because if they are unwilling to lower their LCR ratios below a target level, they can impose losses on MMFs that sell assets and refuse to lend in the interbank market, leading to a market freeze in extreme cases.

In what follows, I will utilise the model to assess whether there exist circumstances under which there can be significant propagation of systemic liquidity risk based on the determinants outlined above.

4.4 Data

4.4.1 MMF data

The main data source for my analysis is iMoneyNet, a database that contains information at the share class and fund levels for the universe of US MMFs. I conduct most of my analysis at the fund level, which may include multiple share classes. The focus of this paper is on prime MMFs, both retail and institutional, that lend to banks. As such I exclude government MMFs from the sample.

First, I download the full portfolio holdings of all US prime MMFs as of the 31st December 2017, after the introduction of the new regulations, in order to coincide with the accounting reporting date of the banks. The holdings contain information at the security level for the issuer, the type (e.g. commercial paper), the maturity date, the MMF that holds it, as well as the market value. I complement this dataset with data extracted from the forms N-MFP which are filed by MMFs monthly in the SEC EDGAR database.[11] Specifically, for each security I identify whether it is DLA, WLA or illiquid. I use this data to calculate the DLA and WLA values of each MMF as a fraction of TNA. Next, I download from iMoneyNet descriptive data for each MMF: whether it is institutional or retail, the identity of its sponsor, and its market and shadow NAVs as of the 31st December 2017. Finally, I download from iMoneyNet monthly data from May 2008 to December 2017 for MMF gross returns and total net assets, which I use to estimate the flow-performance relationship as explained in the previous section.

In Table C.1 in Appendix C.1 the complete list of US prime MMFs is presented along with their TNA and type. There were 66 prime MMFs, 30 institutional and 33 retail, with total net assets of almost $472 billion as of the end of December 2017. A total of 31 MMFs were sponsored by banks, with the rest being sponsored by fund families. Vanguard Prime MMF, a retail fund, was the largest MMF with TNA of $95.794 billion or a fifth of the total TNA.

The breakdown per security type is presented in Table C.2. Certificates of Deposit (CDs) comprised 31% of total value, followed by unsecured commercial paper (CP) issued by financial companies at 21%, non-negotiable time deposits (TDs) at 10% and ABCP at 9%. All these securities are issued by banks or conduits mostly sponsored by banks, which shows the dominance of the financial sector in the issuance of money market instruments.

I identify a total of 616 issuers. Table C.3 presents the top 10 issuers by market value of securities issued. As can be seen, the Federal Reserve Bank of New York and the US Treasury were the largest issuers, comprising 11.29% of total value, followed by various banks. In Figure 4.2 I illustrate the US prime MMF network where the nodes represent the sellers (banks) and buyers (MMFs) of securities. The nodes are connected by total exposures and are weighted by the number of incoming edges, so the issuer nodes with the most MMFs investing in them are the largest ones. The network shows a strong core-periphery structure, with the largest issuers concentrated in the core. This is especially helpful as we don't have to extend the modelling framework far. I identify the largest issuing banks, 66 in number (coincidentally the same as the number of MMFs), which

[11] `https://www.sec.gov/edgar/searchedgar/companysearch.html`

together with the Federal Reserve Bank of New York and the US Treasury, as well as their sponsored ABCP conduits, account for 95.62% of total market value of securities issued. Hence, in this study I focus on this small subset of issuers which nonetheless captures almost the entirety of the market. They are reported in Table C.4 with the total market value of the debt securities issued (excluding those of their sponsored conduits).

4.4.2 Bank data

For each bank, I download data on overnight (on-demand) interbank assets and liabilities as well as their LCR and HQLA from their annual reports, Orbis Bank Focus and SNL Financial as of 31st December 2017. The total interbank assets have a value of $809 billion, while the total interbank liabilities are worth $921 billion. The average LCR across the 66 banks is 148%, while the total HQLA are worth $12.3 trillion. I also download from Bloomberg daily CDS spreads for each bank covering one year, from 31st December 2016 to 31st December 2017. This data is used to calibrate the interbank market in the model.

4.5 Results

4.5.1 Flow-performance relationship

Before I illustrate the simulation results, I briefly discuss the estimation results of the flow-performance relationship (4.3.2) which are presented in Table 4.1. I estimate the regression for the full sample of MMFs as well as splitting into institutional and retail ones.

The fixed effect parameter β is statistically significant in all sample configurations, estimated as 0.692 for the entire sample, 0.937 for institutional MMFs and 0.440 for retail MMFs. As can be seen, institutional MMFs are more than twice as sensitive to past returns than retail ones, with a 1% negative return leading to redemptions of 0.937% and 0.440% respectively. Goldstein et al. (2017) estimate the flow-performance relationship for corporate bond funds equal to 0.859, which lies between my estimates. The conditional R^2, which measures the proportion of flows variability captured by both the fixed and random components, is quite high for the entire sample and the institutional subsample, at 51.3%

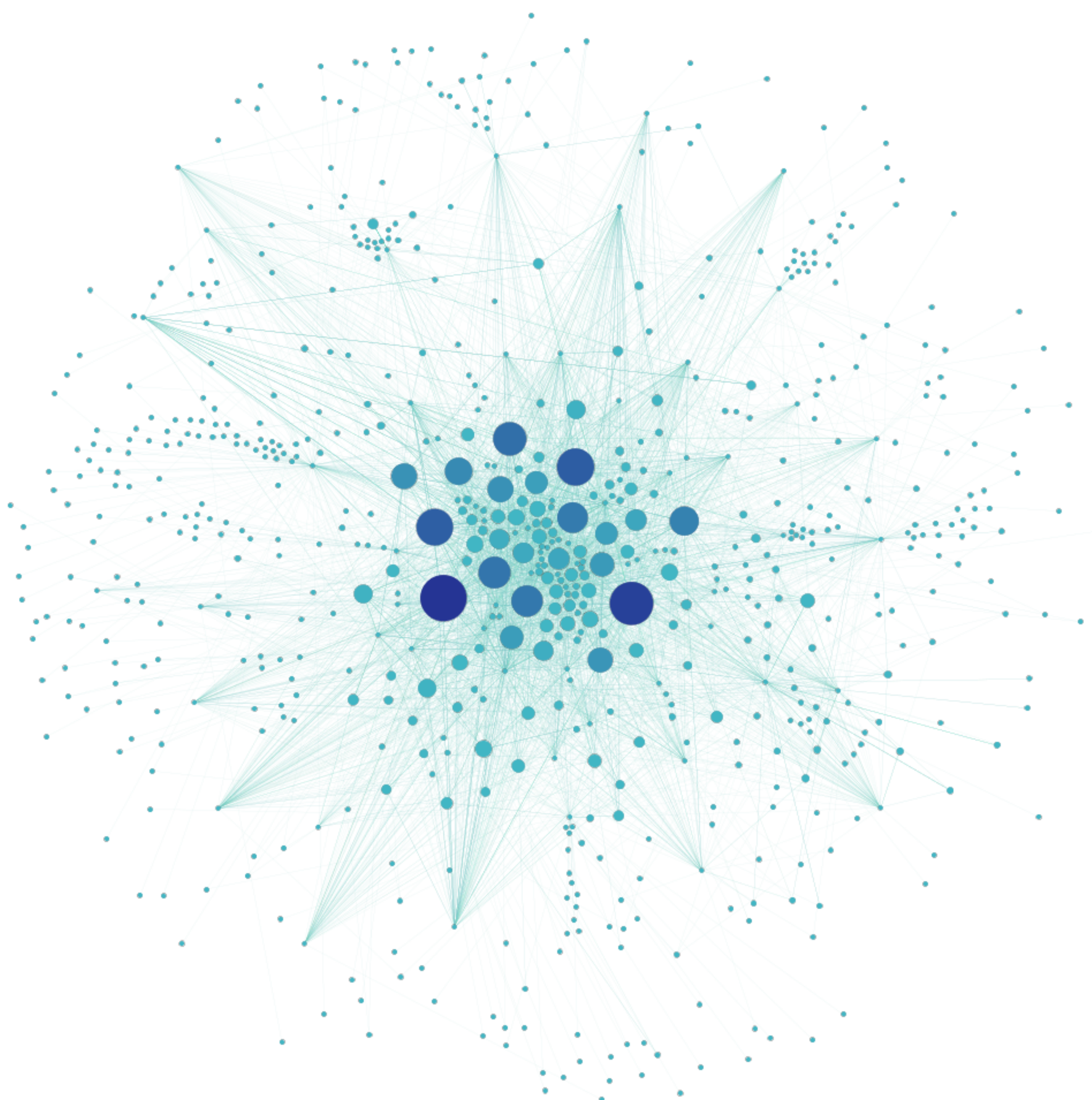

Figure 4.2: The US prime MMF network as of end-December 2017

Nodes represent buyers (MMFs) and sellers (bank issuers) of money market securities and are weighted by the number of incoming edges.
Source: iMoneyNet data and own calculations

Table 4.1: Flow-performance relationship

This table presents the estimates of the flow-performance relationship of the MMF sample with a mixed effects regression using monthly data from May 2008 to December 2017. Column (All) provides results using the entire sample of MMFs while columns (Institutional) and (Retail) split the sample into institutional and retail MMFs only respectively. $Flow_{i,t+1}$ is winsorised at the 1% and 99% levels. t-statistics are provided in parentheses. ***, ** and * signify significance at the 1%, 5% and 10% levels respectively.

	$Flow_{i,t+1}$		
	(All)	(Institutional)	(Retail)
$Return_{i,t}$	0.692***	0.937***	0.440**
	(3.463)	(2.648)	(2.149)
$Log(Fund\ size_{i,t})$	−0.000	−0.002	0.001
	(−0.225)	(−1.249)	(1.088)
$Expense\ ratio_{i,t}$	0.005	−0.006	0.550**
	(0.112)	(−0.112)	(2.453)
$Fund\ age_{i,t}$	−0.001***	−0.001***	−0.000
	(−4.487)	(−4.352)	(−1.545)
$Log(Fund\ family\ size_{i,t})$	−0.000	0.003	−0.001
	(−0.156)	(1.199)	(−0.697)
Intercept	0.009	0.005	−0.010
	(1.036)	(0.240)	(−1.135)
N	6,552	2,798	3,754
Conditional R^2	0.513	0.686	0.014
Marginal R^2	0.188	0.325	0.005

and 68.6% respectively, but lower for the retail subsample at 1.4%. This could be attributed to the fact that the returns of institutional MMFs have a much stronger predictive power on the subsequent flows than the returns of retail MMFs due to the sophistication of their clientele. Comparing the conditional R^2 with the marginal R^2, which measures the proportion of flows variability captured by only the fixed component, we can deduce that the inclusion of random effects substantially increases the explanatory power of the model.

It is interesting to note that a few MMFs in my sample have significant negative random effects u_i's which lower their overall sensitivity to returns. Hence, the model captures the heterogeneity of the flow-performance relationship between MMFs.

4.5.2 Baseline simulation results

In this section I analyse the results of the baseline model presented in section 4.3 for different stress scenarios. Each set of results is an average over 100 simulations due to the randomised asset sale procedure. I set the initial risk-free rate r_0^f equal to the US Libor rate as of end-December 2017 which stood at 1.429%. For ease of presentation, I illustrate the full sets of results in figures provided in Appendix C.2 while a summary of specific results is presented in tables in the main body.

4.5.2.1 Counterparty risk

In this subsection I present the model's results by simulating the default of each bank. I set the lower LCR bound Λ equal to 110% which represents normal market conditions as banks have ample available liquidity to accommodate asset sales.

In Figure C.1 I plot the heatmap of the first-round (negative) percentage NAV returns incurred by the MMFs due to the default of the banks. The banks are sorted according to the value of their issued securities, from the largest issuer (Wells Fargo) to the smallest (US Bancorp). We observe that the larger losses are concentrated in the larger banks, although the largest return of 6.3% is incurred by Meeder MMF due to the default of a relatively small in terms of securities issued bank, Morgan Stanley. This occurs due to a large exposure to the specific bank relative to total assets. In Panel A of Table 4.2, I report the ten largest negative returns, separated by first and subsequent rounds and sorted by total returns. As can be seen, apart from the two largest first-round returns due to the default of Morgan Stanley, the rest are closer to 3%, similar to the losses incurred by RPF due to the default of Lehman Brothers.

The losses due to the banks' default cause some CNAV retail MMFs to break the buck, forcing sponsor banks to provide support. The total support offered by the banks to MMFs for the default of each bank is presented in Figure C.2 (a), separated by first-round and subsequent-rounds support. As can be seen, CNAV MMFs only break the buck due to the initial losses as there is no support offered in subsequent rounds. The default of Bank of Montreal triggers the largest total sponsor support of almost $400 million, which represents less than 0.1% of total MMF TNA.

The negative returns incurred by MMFs not subject to sponsor support generate redemptions from MMFs. In Figure C.2 (b) I present the total TNA losses that are incurred by all MMFs as a result of each bank's default, separated by first-round and subsequent-rounds losses. The former are due to asset devaluations resulting from the banks' default, while the latter are due to redemptions on the second day as by the third day there are no more redemptions in the system. As can be seen, there is a strong association between the magnitude of first-round and subsequent-rounds losses as the former largely dictate the size of the latter. In addition, the amount of total redemptions tends to increase with the size of the bank but it is not the only factor that determines them. Looking at the ten banks whose default creates the largest TNA losses due to redemptions in Panel B of Table 4.2, the largest losses across all MMFs of $13.607 billion occur due to the default of Toronto-Dominion. Wells Fargo, the largest bank by value of assets issued, causes the seventh largest redemptions ($10.112 billion) because a larger fraction of its assets are collateralised. On the other hand, Canadian banks are the dominant issuers of commercial paper which is uncollateralised so they pose the largest counterparty risk to the MMFs. However, even the largest redemption losses originating from the default of Toronto-Dominion represent less than 3% of aggregate TNA across all MMFs, substantially less than the 10% losses observed following Lehman's default.

The redemptions cause MMFs to stop reinvesting the proceeds from maturing securities which creates a funding shortfall for the banks. The total funding shortfall faced by the banks as a result of MMF redemptions is shown in Figure C.2 (c). Since I assume that any MMF that faces redemptions does not reinvest the proceeds from maturing assets on a specific day, the first-round shortfall is a function of the number of MMFs affected due to the default of each bank, rather than its size in the money markets. As a result, we can deduce that Bank of Montreal is the most interconnected bank affecting the greatest number of MMFs and creating a funding shortfall for the remaining banks of $76.408 billion in the first round, and reaching $80.968 billion overall, or 0.659% of total bank HQLA. Once again, Wells Fargo is not in the top five contributors which highlights the fact that, although related, the amount of assets issued is not a perfect indicator of the potential of a bank to create stress in the system.

Next, I assess the MMFs' ability to honour redemption using liquid resources and the extent to which they resort to asset sales. Figure C.3 (a) shows the value of assets sold from MMFs to banks in case of default of each bank. In most cases, these remain zero as MMFs have enough liquidity to accommodate redemptions without breaking their regulatory limit of 30% WLA. The default of Toronto-Dominion causes the largest asset sales but they are limited to $24 million, around half a basis point of total MMF assets. These results showcase the high liquidity reserves that MMFs hold as a result of post-crisis regulations. Given the small amount of assets sold, and the fact that banks do not hoard liquidity in this stress scenario, the average haircut that is applied in all cases is 0% as seen in Figure C.3 (b). As a result the banks buy back the assets at market value and no MMF breaches the 30% WLA bound, so none of them imposes a liquidity fee on redemptions.

In Figure C.4 I illustrate the cumulative returns occurring from days 2 to 5, i.e. excluding the initial losses due to the banks' default in order to assess the effect of fire sales on total returns. As can be seen, returns are practically zero for subsequent days since the banks do not impose haircuts and there are no fire sales losses. Nonetheless, the zero returns do not imply that no redemptions occur in subsequent days, rather that these do not cause further reduction to NAV because they only occur in VNAV MMFs at market prices, either institutionals or retails that broke the buck and became VNAV. Sponsored CNAV MMFs in danger of breaking the buck in the first round receive enough support so that they retain their $1 valuation and so experience no further redemptions.

Finally, banks' HQLA reserves are reduced by the support offered to stressed MMFs and the funding shortfall. However, these losses are balanced by the additional gains realised through increased interbank lending. In Figure C.3 (c) I present the aggregate HQLA losses due to the default of each bank. The first-round losses are due to the initial support offered to CNAV MMFs in danger of breaking the buck while the subsequent losses are due to the interest payments on higher interbank liabilities resulting from the funding shortfall as well as any subsequent support and purchases of MMF assets. Looking at Panel C of Table 4.2, the largest losses occur once again due to the default of Bank of Montreal ($1.213 billion) but they represent only 1 basis point of the overall HQLA reserves. As a result, none of the banks breaches the lower LCR threshold of 110% and the equilibrium rate r_t^f remains constant throughout the five days in all simulations.

To summarise, the initial losses incurred by MMFs due to an issuer's default do not have significant subsequent-rounds effects when banks facilitate market liquidity and support CNAV MMFs. The ample liquidity held by the MMFs makes them capable to honour the majority of redemption requests without resorting to significant asset sales.

4.5.2.2 Liquidity risk

The previous analysis assumes that investors act according to a pre-determined flow-performance relationship. However, as was evidenced during the financial crisis, what drove the mass redemption requests were the strategic complementarities arising due to the structural characteristics of the MMFs rather than any realised losses (Schmidt et al., 2016). In addition, investors may decide to redeem their capital in search for cash as was evidenced during the recent Covid-19 crisis. In order to simulate such scenarios, in this subsection I impose large exogenous outflows on the MMFs while remaining agnostic about the reason behind them. In addition, due to the large resulting funding shortfalls I assume that banks decide to hoard liquidity by setting the lower LCR bound Λ equal to 116%.[12]

I consider a range of redemption shock scenarios, starting from uniform outflows of 10% of TNA from institutional MMFs and 2% of TNA from retail MMFs, increasing the former by 2% and the latter by 1% up to an extreme scenario of 50% of TNA redemptions for institutional MMFs and 22% of TNA redemptions for retail MMFs. Such extreme scenarios are beyond any historical precedence. Nonetheless, this analysis is useful in determining the capacity of the banks to withstand severe funding shortfalls as well as their ability to accommodate asset sales during a wider run on prime MMFs.

[12]Beyond that point the equilibrium rate becomes unstable indicating a complete market freeze.

Table 4.2: Summary of results for counterparty risk

This table presents the summary results for counterparty risk including the largest negative MMFs' returns in the first and subsequent rounds, the largest total MMFs' TNA losses and the largest total banks' HQLA losses for the corresponding defaulting bank.

Panel A: Largest negative MMF returns

Defaulting bank	**MMF**	**Return (First/Subsequent) (%)**
Morgan Stanley	Meeder MMF	6.341/0.000
Morgan Stanley	Meeder Institutional Prime MMF	4.615/0.000
Toronto-Dominion	Invesco Liquid Assets Portfolio	3.593/0.000
Bank of Montreal	Dreyfus Inst Preferred MMF	3.437/0.000
Toronto-Dominion	Dreyfus Cash Management	3.299/0.000
Barclays	BlackRock MMP	3.293/0.000
National Bank of Canada	Morgan Stanley Instit Liquidity/Prime	3.121/0.000
Canadian Imperial Bank of Commerce	Federated Capital Reserves Fund	3.114/0.000
JPMorgan	Goldman Sachs FS MMF	3.101/0.000
Toronto-Dominion	Northern Instit Prime Obligs Port	3.079/0.000

Panel B: Largest TNA losses

Defaulting bank	**TNA losses ($bn)**	**% of total TNA**
Toronto-Dominion	13.607	2.885
Canadian Imperial Bank of Commerce	13.606	2.884
RBC	12.951	2.746
Bank of Nova Scotia	12.327	2.613
ANZ Banking Group	11.171	2.368
Mitsubishi UFJ Financial Group	10.670	2.262
Wells Fargo	10.112	2.144
Sumitomo Mitsui Banking Corp	9.562	2.027
Bank of Montreal	9.426	1.998
Commonwealth Bank of Australia	7.908	1.677

Panel C: Largest HQLA losses

Defaulting bank	**HQLA losses ($bn)**	**% of total HQLA**
Bank of Montreal	1.213	0.010
Toronto-Dominion	1.042	0.009
Canadian Imperial Bank of Commerce	1.018	0.008
Wells Fargo	0.998	0.008
Sumitomo Mitsui Trust Bank	0.827	0.007
Sumitomo Mitsui Banking Corp	0.756	0.006
Mizuho	0.710	0.006
Bank of Nova Scotia	0.668	0.005
Northern Trust	0.665	0.005
ANZ Banking Group	0.645	0.005

As before, I start with the first-round negative MMF returns in Figure C.5, which occur due to the initial redemption shocks and losses from the subsequent asset sales. The heatmap provides an interesting overview of the vulnerability of MMFs to fire sales due to liquidity constraints. As can be seen, while most MMFs are resilient even when faced with very large redemptions, certain MMFs like Meeder Institutional Prime MMF and JPMorgan Prime MMF incur large negative returns of 12.7% and 9.4% respectively. In fact, these two MMFs comprise the ten largest total negative returns as seen in Table 4.3 Panel A. Interestingly, Meeder's losses do not seem to stem from a lack of excess WLA (48.8% as of December 2017) but rather due to its exposure to banks that impose steep haircuts. A simple correlation analysis reveals that the average correlation across all shock scenarios and MMFs of the negative first-round returns with the respective baseline WLAs is -8.85% while the correlation with the average haircut imposed across all asset sales is 70.03%. This suggests that banks' unwillingness to accommodate asset sales following a large redemption shock can cause MMFs to incur severe losses even when they have large liquidity buffers in the absence of a regulatory authority acting as buyer of last resort.

The sponsor support offered to retail MMFs in danger of breaking the buck as a result of the first-round losses is presented in Figure C.6 (a). It reaches \$13 million in the most severe shock scenario, significantly lower than the amount of \$400 million observed when considering counterparty risk in the previous subsection. This is because of the retail MMFs' ample liquidity which allows them to satisfy the majority of redemptions without resorting to asset sales and facing losses.

Figure C.6 (b) shows the total TNA losses of MMFs due to the different redemption shocks. The first-round losses are a function of the severity of the exogenous shock, ranging from \$26 billion to \$165 billion. The subsequent-rounds losses are zero for the mild redemption shocks but gradually increase with the severity of the shock reaching \$4 billion in the most severe case. This reflects the difficulty of the banks to accommodate increasing asset sales and the subsequent increase in haircuts that they impose, leading to higher fire sales losses and redemptions. The ten largest TNA losses are presented in Table 4.3 Panel B. The most extreme redemption shock wipes out \$168.849 billion or more than a third of total TNA (35.797%), around three times more severe than the shock of September 17 2008.

The funding shortfall generated by the decision of MMFs under stress to stop reinvesting the proceeds from maturing securities is presented in Figure C.6 (c). As can be seen, it is the same for all shock scenarios in the first round at \$82 billion because it is a function of the number of MMFs affected by redemptions rather than the magnitude of the redemption shock. The subsequent-rounds shortfall gradually increases with the shock magnitude from \$1 billion to \$14 billion as more MMFs are affected by fire sales and suffer further redemptions.

As a result of the redemptions, MMFs are forced to sell large amounts of assets to the banks to raise cash and not breach the 30% WLA threshold. These increase quickly from negligible to \$64 billion or 13.5% of total MMF TNA in the first round as seen in Figure C.7 (a). Subsequent-rounds sales similarly rise up to \$6 billion. The combination of a large funding shortfall and asset sales together with banks' liquidity hoarding behaviour makes them impose steep haircuts as seen in Figure C.7 (b), averaging 85% in the first round and 58% in subsequent rounds across all shock scenarios. As a result, several MMFs are forced to impose liquidity fees to prevent their WLA dropping below 30%, with the average fee imposed being 1.04% in the first round and 0.34% in subsequent rounds. The subsequent-rounds returns are presented in Figure C.8 and remain subdued as the subsequent redemptions are determined according to the flow-performance relationship (4.3.2) so the fire sales losses from asset sales are lower. However, the two most affected MMFs in the first round, Meeder Institutional Prime MMF and JPMorgan Prime MMF, continue to incur significant negative returns of 4.5% and 2.1% respectively as they suffer higher subsequent redemptions due to their high initial losses.

Finally, the banks' HQLA losses are presented in Figure C.7 (c) which follow a similar increasing pattern as the shock magnitude increases. Looking at Table 4.3 Panel C, the largest losses reach \$64.964 billion, or 0.529% of total HQLA. While significant, these losses still do not force any bank to breach the regulatory LCR threshold of 100%, although several drop below 116%. This is despite an increase to the cost of funding in the interbank market as the equilibrium rate r_t^f rises to 3.1% due to liquidity hoarding, which is similar to the level of US Libor in early 2008 bur lower than its peak in September 2008 of 6.8%.

Overall, the results indicate that large MMF redemption shocks can have a significant but not systemically destabilising effect for banks even if they hoard liquidity. There are various reasons for this. First, the prime MMF sector has reduced significantly in size following the adoption of the new regulations as seen in Figure 4.1. Second, both MMFs and banks have considerably increased their available liquidity which helps mitigate the negative effects of redemptions. And third, the new MMF regulations help reduce subsequent-rounds redemptions.

Table 4.3: Summary of results for liquidity risk

This table presents the summary results for liquidity risk including the largest negative MMFs' returns in the first and subsequent rounds, the largest total MMFs' TNA losses and the largest total banks' HQLA losses for the corresponding exogenous redemption shock.

Panel A: Largest negative MMF returns

Redemption (% of MMF TNA)	MMF	Return (First/Subsequent) (%)
50	Meeder Institutional Prime MMF	12.730/4.548
48	Meeder Institutional Prime MMF	11.289/4.050
46	Meeder Institutional Prime MMF	9.610/3.734
44	Meeder Institutional Prime MMF	9.138/2.828
50	JPMorgan Prime MMF	9.396/2.055
48	JPMorgan Prime MMF	8.575/2.079
42	Meeder Institutional Prime MMF	7.866/2.151
46	JPMorgan Prime MMF	7.943/1.597
40	Meeder Institutional Prime MMF	7.083/1.897
44	JPMorgan Prime MMF	7.039/1.547

Panel B: Largest TNA losses

Redemption (Instit./Retail % of TNA)	TNA losses ($bn)	% of total TNA
50/22	168.849	35.797
48/21	161.526	34.244
46/20	154.014	32.652
44/19	146.363	31.030
42/18	139.260	29.524
40/17	131.989	27.982
38/16	124.743	26.446
36/15	117.511	24.913
34/14	110.129	23.348
32/12	103.145	21.867

Panel C: Largest HQLA losses

Redemption (Instit./Retail % of TNA)	HQLA losses ($bn)	% of total HQLA
50/22	64.964	0.529
48/21	59.933	0.488
46/20	54.801	0.446
44/19	49.483	0.403
42/18	44.873	0.365
40/17	40.528	0.330
38/16	36.276	0.295
36/15	32.057	0.261
34/14	27.863	0.227
32/12	24.248	0.197

4.5.3 No MMF regulations

A question that naturally arises from the previous analysis is what is the key driver behind the results. To what extent is the ability of the banking sector to withstand liquidity shocks driven by the high HQLA reserves irrespectively of the MMF regulations? In order to answer this question, I run a counterfactual analysis. Using the same dataset, I run the model assuming that the MMF regulations have not been implemented, i.e. all MMFs are CNAV and there are no rules for liquidity fees, as was the case during the financial crisis. In addition, in order to take into account the endogenous reaction of the MMF investors to the new regulations, i.e. the massive outflows that occurred in the run-up to their introduction, I scale the prime MMF sector's TNA to their 2010 level of \$1.62 trillion (ICI, 2018). By scaling the 2017 MMF holdings, I thus assume that in the absence of the new regulations the MMFs would have similar portfolio compositions but roughly 3.5 times more capital to invest. This is reasonable to assume as by 2010 the SEC had already imposed minimum liquidity requirements to the MMFs which forced them to diversify their holdings to US Treasuries and repos instead of exclusively corporate debt (ICI, 2016). I do not calibrate the model to 2010 data for two reasons: first, because detailed MMF holdings data from this period are not available; and second, because the aim of this analysis is to assess the effectiveness of the post-crisis LCR regulation in isolation of the MMF regulations. I assume that banks do not hoard liquidity in this simulation, i.e. setting the lower LCR bound Λ to 110%, although the results are qualitatively similar if it is set to 116%.

Without the MMF regulations, the investors have the incentive to front-run others if the MMF faces losses as explained in section 4.2. I modify my model to capture the emerging dynamics of MMF runs theoretically described and empirically verified by Schmidt et al. (2016). The authors look at the individual share classes of each MMF which can be institutional or retail and find that institutional investors were more prone to withdraw their capital than retail investors within the same fund during the crisis. They also find that as the fraction of total assets held by institutional investors within each MMF increased, the total outflows also increased because of the strategic complementarities arising due to their sophistication.

I perform this analysis at the share class level. Each MMF can have multiple share classes, classified either as institutional or retail. The former typically require large minimum deposits ($\geq$ \$100,000) but enjoy smaller expense ratios (fund fees) compared to the retail ones. If an MMF breaks the buck following a bank's default, I assume that institutional investors will attempt to redeem at par and immediately withdraw all of their funds (similar to the RPF case). Retail investors will instead only redeem according to the flow-performance relationship as before as they do not monitor market conditions to the same extent. In order to scale the total TNA to the 2010 levels, I multiply each holding's market value by the fraction of 2010 TNA to 2017 TNA, i.e. a scaling factor equal to 3.435.

Starting with the first-round negative returns in Figure C.9, which include the redemptions as a result of the asset losses from the banks' default, it can be observed that the MMFs that do not receive sponsor support and break the buck experience a complete withdrawal of institutional capital. This leads them to post very large negative returns, reaching 100% if they are entirely comprised of institutional capital. MMFs that are predominantly institutional but also contain retail capital in multiple share classes (e.g. BlackRock Liquidity:TempFund and Federated Instit Money Market Mgmt) post lower but still significant first-round negative returns because of the flight of institutional capital.

Table 4.4: Summary of results for no MMF regulations

This table presents the summary results assuming there are no MMF post-crisis regulations including the largest negative MMFs' returns in the first and subsequent rounds and the largest total banks' HQLA losses for the corresponding defaulting bank.

Panel A: Largest TNA losses		
Defaulting bank	**TNA losses ($bn)**	**% of total TNA**
Toronto-Dominion	450.447	27.803
Wells Fargo	444.444	27.431
Bank of Nova Scotia	440.130	27.164
Canadian Imperial Bank of Commerce	433.685	26.767
ANZ Banking Group	418.895	25.854
RBC	401.557	24.784
Mitsubishi UFJ Financial Group	390.618	24.109
Bank of Montreal	388.574	23.983
Mizuho	377.800	23.318
Sumitomo Mitsui Banking Corp	370.948	22.895
Panel B: Largest HQLA losses		
Defaulting bank	**HQLA losses ($bn)**	**% of total HQLA**
Toronto-Dominion	169.493	1.380
Canadian Imperial Bank of Commerce	165.687	1.349
ANZ Banking Group	159.911	1.302
Wells Fargo	154.426	1.257
Bank of Nova Scotia	153.306	1.248
Mizuho	153.059	1.246
Sumitomo Mitsui Banking Corp	151.601	1.234
RBC	142.275	1.159
Mitsubishi UFJ Financial Group	138.125	1.125
Bank of Montreal	134.175	1.093

The sponsor support offered to MMFs is presented in Figure C.10 (a), which is higher than in the previous simulations due to the larger size of the MMF sector and the fact that all MMFs are CNAV. Specifically, it reaches $7 billion if Toronto-Dominion defaults, considerably higher than the $4.4 billion of support provided in total from 2007 to 2011 to US MMFs (Brady et al., 2012).

Figure C.10 (b) presents the total TNA losses. The first-round losses due to each bank's default are completely dominated by the subsequent-rounds losses due to the run of institutional investors. This is similar to what occurred during the financial crisis when a 3% capital loss incurred by RPF investors due to the default of Lehman Brothers led to massive redemption requests. As seen in Table 4.4 Panel A, the total losses reach $450.447 billion when Toronto-Dominion defaults, or 27.803% of total TNA, similar in magnitude as during the financial crisis.

The funding shortfall in the first round reaches $190 billion with the default of Bank of Nova Scotia as seen in Figure C.10 (c), identifying it as the most interconnected bank in this simulation.[13] When considering the total funding shortfall, it reaches $238 billion with the default of the same bank, or 1.94% of total HQLA.

MMFs retain their high liquidity in this stress scenario but have to resort to significant asset sales to satisfy redemptions as seen in Figure C.11 (a). The default of Toronto-Dominion causes the largest asset sales of $160 billion, or 10% of total MMF TNA. The pressure on the banks' liquidity forces them to impose large haircuts on the asset sales even in the absence of liquidity hoarding, averaging 52% in the first round but subduing in subsequent rounds (Figure C.11 (b)). The subsequent-rounds returns, presented in Figure C.12, shows that the MMFs that suffered a significant but not total flight of capital (e.g. BlackRock Liquidity:TempFund and Federated Instit Money Market Mgmt) also post large

[13]This is different from Bank of Montreal in subsection 4.5.2.1 because the subset of MMFs receiving support is different, which affects which ones stop reinvesting and the resulting funding shortfall.

negative returns in subsequent rounds. This is exactly because of the negative externality imposed on the remaining investors due to the run as the NAV is further reduced and the MMFs are forced to resort to fire sales to satisfy redemptions.

Finally, the overall HQLA losses for the banks reach $169.493 billion when Toronto-Dominion defaults, which represents 1.380% of total available HQLA as seen in Table 4.4 Panel B and Figure C.11 (c). While this amount is significant, it still does not force any bank to post an LCR lower than 100%. In addition, the equilibrium rate of the interbank market remains constant throughout the stress scenario. As a result, this analysis shows that the introduction of the LCR has enhanced the capacity of the banking sector to withstand liquidity shocks of similar magnitude as the one originating from MMFs during the crisis.

4.5.4 Robustness tests

In order to test the sensitivity of the results to different model specifications, I have run a number of robustness tests. First, I have repeated the analysis by also including the capital and leverage constraints outlined in the Basel III framework.[14] The results are qualitatively and quantitatively similar as none of the banks breach the minimum regulatory thresholds of 8% and 3% for the capital and leverage ratios respectively as a result of the increased interbank activity.

Second, I have run the model assuming there is no interbank market, so the banks deduct the entire funding shortfall from their HQLA and do not offset these losses via gains from interbank lending. While this more than doubles the total HQLA losses, none of the banks post an LCR less than 100% (even under the scenario of no MMF regulations and increased size of the MMF sector).

Third, I have also run the model assuming that the MMF regulations are imposed but

[14] https://www.bis.org/bcbs/basel3.htm

the sector's size is the same as in 2010 in order to determine whether the reduction of the size was an important factor in reducing its systemicness. The results remain qualitatively similar as in subsection 4.5.2.1 which indicates that this is not the case.

Overall, the tests indicate that my main results are not driven by model assumptions but reflect the increased resilience of the banking system to liquidity shocks.

4.6 Conclusion

In this paper I have developed a framework to assess the resilience of the US prime MMFs faced with counterparty and liquidity risks as well as their potential to transmit stress to the banking sector by cutting wholesale funding. Using end-2017 data, I document the resilience of the MMF sector in all but the most extreme redemption shocks as well as the ability of the banks to retain enough liquidity to satisfy their LCR regulatory requirements.

The results indicate that the LCR requirement introduced in Basel III makes the banks able to withstand the funding shocks originating from the MMF sector. Hence, from a macroprudential perspective, systemic liquidity risk originating from the interconnectedness of banks with US prime MMFs has decreased. In addition, the post-crisis regulations have made US prime MMFs more resilient to shocks by adhering to strict minimum liquidity and diversification criteria. However, they can still face severe losses if the banks are unwilling to accommodate asset sales and in the absence of a buyer of last resort, which can amplify the propagation of liquidity stress.

These findings contrast with what was observed during the run on US prime MMFs at the height of the financial crisis when there were severe repercussions for the banks and the real economy. While the increased liquidity reserves of the banks have enhanced their resilience, my analysis remains partial in nature as it does not consider other funding markets that were also stressed during the crisis. In addition, the new MMF regulations have reduced the incentive for investors to front-run others when mass redemptions occur but as seen in the recent Covid-19 crisis such an event cannot be ruled out, especially given their strong preference for capital preservation and aversion for liquidity fees. As such, future research should focus on more detailed modelling of amplification mechanisms between different money markets and assessing their implications for financial stability.

Appendix C

C.1 Data summary

Table C.1: List of US prime MMFs

This table lists all US prime MMFs as of December 2017, with their total net assets, the % share of total TNA across all MMFs, their type and whether they are sponsored by banks.

Money Market Fund	**TNA ($bn)**	**Share of total (%)**	**Type**	**Bank sponsored**
Vanguard Prime MMF	95.794	20.309	Retail	No
BlackRock Money Market Master Portfolio	56.101	11.894	Institutional	No
JPMorgan Prime MMF	37.206	7.888	Institutional	Yes
Schwab Cash Reserves	35.875	7.606	Retail	No
Schwab Value Advantage MF	27.485	5.827	Retail	No
Fidelity Inv Money Market Portfolio	25.798	5.469	Retail	No
Western Asset Liquid Reserves	19.374	4.107	Institutional	Yes
Fidelity MMF	14.672	3.111	Retail	No
Schwab Advisor Cash Reserves	14.413	3.056	Retail	No
Fidelity Inv Prime MMP	13.602	2.879	Institutional	No
BlackRock Liquidity:TempFund	13.581	2.879	Institutional	No
State Street Money Market Portfolio	9.936	2.106	Institutional	Yes
General MMF	9.149	1.940	Retail	Yes
Schwab Money Market Fund	7.997	1.695	Retail	No
Federated Prime Cash Obligs	7.091	1.503	Retail	No
Federated Instit Prime Oblig	6.841	1.450	Institutional	No
Wells Fargo Heritage MMF	6.710	1.422	Institutional	Yes
UBS Prime Master Fund	6.458	1.369	Institutional	Yes
Dreyfus Cash Management	5.902	1.251	Institutional	Yes
Federated Capital Reserves Fund	5.278	1.119	Retail	No
Morgan Stanley Instit Liquidity/Prime	5.017	1.064	Institutional	Yes
USAA Money Market Fund	4.395	0.932	Retail	No

Table C.1: List of US prime MMFs (continued)

Money Market Fund	TNA ($bn)	Share of total (%)	Type	Bank sponsored
Fidelity Inv Prime Reserves	3.697	0.784	Institutional	No
First Amer Retail Prime Obligs Fund	2.952	0.626	Retail	Yes
Dreyfus Inst Preferred MMF	3.055	0.648	Institutional	Yes
Invesco Liquid Assets Portfolio	2.831	0.600	Institutional	No
Goldman Sachs FS MMF	2.424	0.514	Institutional	Yes
T Rowe Price Cash Reserves Fund	2.263	0.480	Retail	No
Northern Instit Prime Obligs Port	2.220	0.471	Institutional	Yes
JPMorgan Liquid Assets MMF	1.950	0.413	Retail	Yes
BlackRock Liquidity:TempCash	1.823	0.386	Institutional	No
UBS Prime CNAV Master Fund	1.849	0.392	Retail	Yes
Wells Fargo Cash Invmt MMF	1.499	0.318	Institutional	Yes
Ivy Cash Mgmt Fund	1.465	0.311	Retail	No
Goldman Sachs FS Prime Obligs Fund	1.394	0.296	Institutional	Yes
Schwab Variable Share Price MF	1.295	0.275	Institutional	No
American Century Prime MMF	1.269	0.269	Retail	No
TD Money Market Portfolio	1.131	0.240	Retail	No
Putnam MMF	0.822	0.174	Retail	No
First Amer Instit Prime Obligations	0.784	0.166	Institutional	Yes
Morgan Stanley Instit Liq/MMP	0.786	0.167	Institutional	Yes
DWS Money Market Prime Series	0.774	0.164	Retail	Yes
Invesco Premier Portfolio	0.740	0.157	Retail	No
Dreyfus Liquid Assets	0.618	0.131	Retail	Yes

Table C.1: List of US prime MMFs (continued)

Money Market Fund	TNA ($bn)	Share of total (%)	Type	Bank sponsored
Schwab Investor Money Fund	0.568	0.120	Retail	No
Principal Funds MMF	0.484	0.103	Retail	No
Wells Fargo Money Market Fund	0.474	0.100	Retail	Yes
BlackRock MMP	0.473	0.100	Retail	No
BMO Prime MMF	0.451	0.096	Retail	Yes
BMO Institutional Prime MMF	0.419	0.089	Institutional	Yes
Invesco Prime Portfolio	0.378	0.080	Institutional	No
Goldman Sachs Inv MMF	0.333	0.071	Retail	Yes
MainStay Money Market Fund	0.330	0.070	Retail	No
Meeder Institutional Prime MMF	0.297	0.063	Institutional	No
Northern MMF	0.211	0.045	Retail	Yes
Schwab Retirement Advantage MF	0.201	0.043	Retail	No
Dreyfus Prime MMF	0.155	0.033	Retail	Yes
Dreyfus BASIC MMF	0.129	0.027	Retail	Yes
Western Asset Prime Oblig MMF	0.128	0.027	Retail	Yes
DWS Variable NAV MF	0.122	0.026	Institutional	Yes
Federated Instit Money Market Mgmt	0.085	0.018	Institutional	No
Plan Inv Fund/MMP	0.065	0.014	Institutional	No
Meeder MMF	0.035	0.007	Retail	No
T Rowe Price Instit Cash Reserves	0.021	0.004	Institutional	No
Federated Inst Prime 60 Day Fund/Pm	0.008	0.002	Institutional	No
Morgan Stanley Active Assets Prime Trust	0.003	0.001	Retail	Yes
Total	**471.687**	**100**		

Source: iMoneyNet data and own calculations

Table C.2: Security type breakdown

This table lists the security types US prime MMFs invested to as of December 2017, the total value invested and the % share of total.

Security type	**Market value ($bn)**	**Share of total (%)**
CD	144.894	30.718
Financial Co CP	97.998	20.776
Non-Negotiable TD	47.658	10.104
ABCP	40.714	8.632
Other Repo	36.329	7.702
Treasury Repo	32.810	6.956
Treasury Debt	26.271	5.570
Other CP	13.211	2.801
VRDN	8.897	1.886
Govt Agency Repo	8.569	1.817
Other Instrument	7.288	1.545
Govt Agency Debt	3.083	0.654
Cash	1.596	0.338
Tender Option Bond	1.311	0.278
Non-US SUPRA	0.526	0.112
Other Muni Debt	0.200	0.042
Investment Co	0.166	0.035
Other ABS	0.148	0.031
Ins Co Funding Agrmnt	0.017	0.004
Total	**471.687**	**100**

Source: iMoneyNet data and own calculations

Table C.3: Top 10 issuers by market value of securities issued

This table lists the ten largest issuers of money market securities bought by US prime MMFs as of December 2017, the total value issued and the % share of total.

Issuer	**Market value ($bn)**	**Share of total (%)**
Federal Reserve Bank of NY	26.965	5.717
US Dept of the Treasury	26.271	5.570
Wells Fargo	19.647	4.165
RBC	16.496	3.497
Toronto-Dominion	14.936	3.166
Canadian Imperial Bank of Commerce	14.077	2.984
Bank of Nova Scotia	13.605	2.884
Mitsubishi UFJ Financial Group	12.059	2.557
ANZ Banking Group	11.616	2.463
Bank of Montreal	10.951	2.322
Total	**166.623**	**35.325**

Source: iMoneyNet data and own calculations

Table C.4: List of banks

This table lists the 66 largest issuer banks of money market securities bought by US prime MMFs as of December 2017, the total value issued, the % share of total and whether they sponsor MMFs.

Issuer	**Market value ($bn)**	**Share of total (%)**	**Sponsor bank**
Wells Fargo	19.647	4.165	Yes
RBC	16.496	3.497	No
Toronto-Dominion	14.936	3.166	Yes
Canadian Imperial Bank of Commerce	14.077	2.984	No
Bank of Nova Scotia	13.605	2.884	No
Mitsubishi UFJ Financial Group	12.059	2.557	No
ANZ Banking Group	11.616	2.463	No
Bank of Montreal	10.951	2.322	Yes
Citigroup	10.036	2.128	Yes
Sumitomo Mitsui Banking Corp	9.643	2.044	No
Mizuho	9.264	1.964	No
Barclays	9.223	1.955	No
HSBC	8.112	1.720	No
Bank of America	8.071	1.711	No
JPMorgan	7.911	1.677	Yes
Nordea Bank	7.800	1.654	No
Sumitomo Mitsui Trust Bank	7.731	1.639	No
Credit Agricole	7.495	1.589	No
Commonwealth Bank of Australia	7.432	1.576	No
BNP Paribas	7.305	1.549	No
Westpac	7.260	1.539	No
UBS	6.944	1.472	Yes

Table C.4: List of banks (continued)

Issuer	**Market value ($bn)**	**Share of total (%)**	**Sponsor bank**
National Australia Bank	6.835	1.449	No
Credit Suisse	6.730	1.427	No
DnB NOR Bank	6.095	1.292	No
Svenska Handelsbanken	5.246	1.112	No
Swedbank	5.149	1.092	No
ABN AMRO	4.828	1.024	No
KBC Bank	4.529	0.960	No
Oversea-Chinese Banking Corp	4.399	0.933	No
Landesbank Baden-Wuerttemberg	4.299	0.897	No
Skandinaviska Enskilda Banken	3.952	0.838	No
Societe Generale	3.612	0.766	No
BPCE	3.492	0.740	No
Norinchukin Bank	3.287	0.697	No
ING	3.101	0.658	No
Standard Chartered Bank	2.967	0.629	No
DBS Bank	2.940	0.623	No
Rabobank	2.833	0.601	No
Natixis	2.505	0.531	No
Bayerische Landesbank	2.289	0.485	No
State Street	2.262	0.479	Yes
NRW.Bank	2.128	0.451	No
National Bank of Canada	2.063	0.437	No

Table C.4: List of banks (continued)

Issuer	**Market value ($bn)**	**Share of total (%)**	**Sponsor bank**
Deutsche Bank	1.952	0.414	Yes
Danske Corp	1.779	0.377	No
Helaba	1.769	0.375	No
Dexia	1.530	0.324	No
Credit Industriel et Commercial	1.459	0.309	No
China Construction Bank	1.409	0.299	No
United Overseas Bank	1.395	0.296	No
Industrial & Commercial Bank of China	1.279	0.271	No
Santander UK	1.165	0.247	No
Northern Trust	1.137	0.241	Yes
Lloyds Banking Group	1.094	0.232	No
Macquarie Group	1.082	0.229	No
Morgan Stanley	1.048	0.222	Yes
First Abu Dhabi Bank	0.940	0.199	No
DZ Bank	0.918	0.195	No
Bank of China	0.880	0.186	No
Goldman Sachs	0.646	0.137	Yes
Bank Nederlandse Gemeenten	0.413	0.088	No
RBS	0.392	0.083	No
Chiba Bank	0.376	0.080	No
BNY Mellon	0.067	0.014	Yes
US Bancorp	0.031	0.007	Yes
Total	**335.846**	**71.201**	

Source: iMoneyNet data and own calculations

C.2 Figures

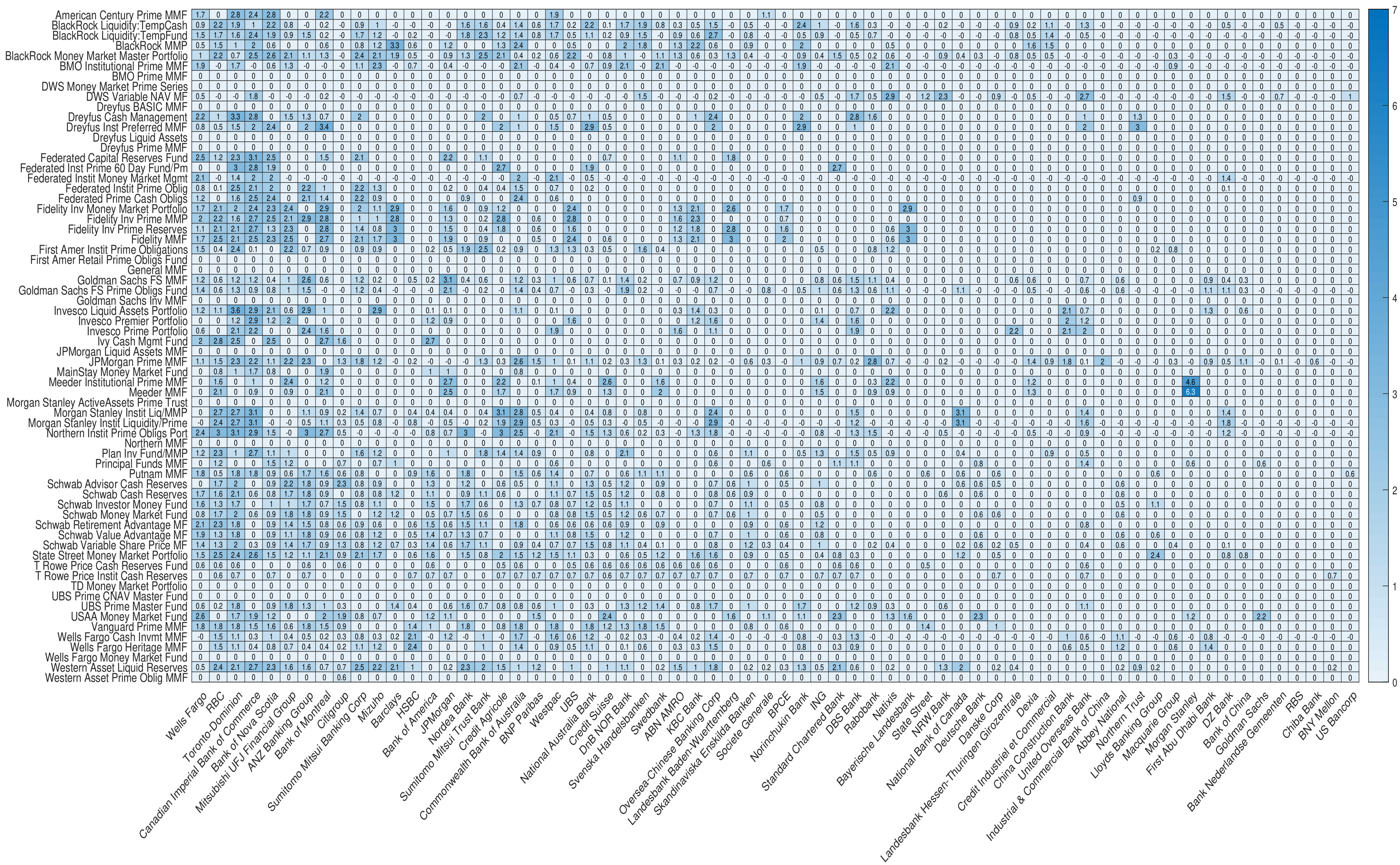

Figure C.1: First-round MMF returns (counterparty risk)

This figure presents the first-round negative MMF returns in % due to asset losses after the default of each corresponding bank.

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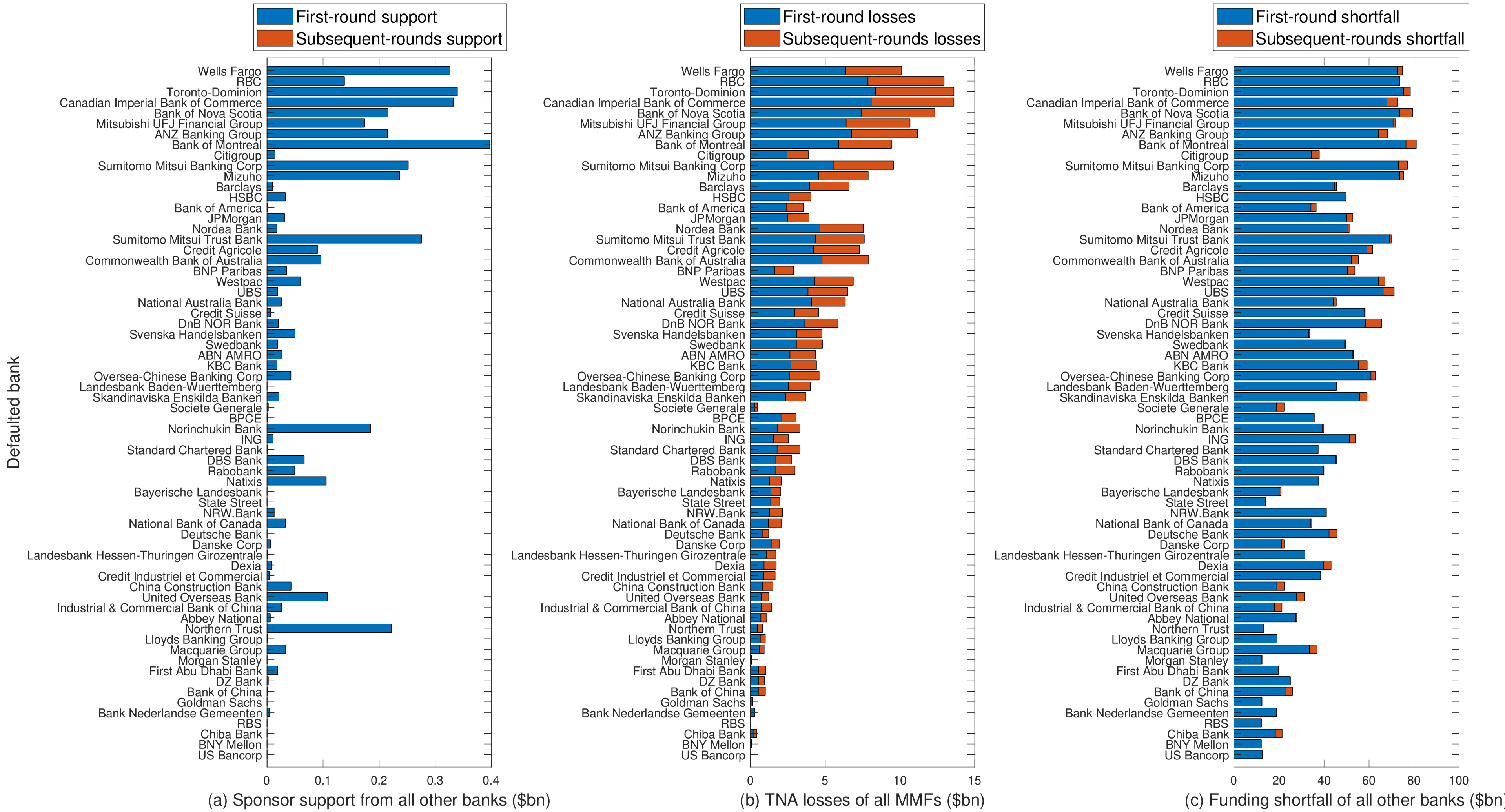

Figure C.2: Summary of results 1 (counterparty risk)

Subfigure (a) presents the total sponsor support offered by banks to CNAV MMFs in danger of breaking the buck after the default of each corresponding bank. Subfigure (b) presents the total MMF TNA losses due to assets' devaluation after the default of each corresponding bank (first round) and due to secondary redemptions (subsequent rounds). Subfigure (c) presents the total funding shortfall of banks following the withdrawal of funding by MMFs facing redemptions after the default of each corresponding bank.

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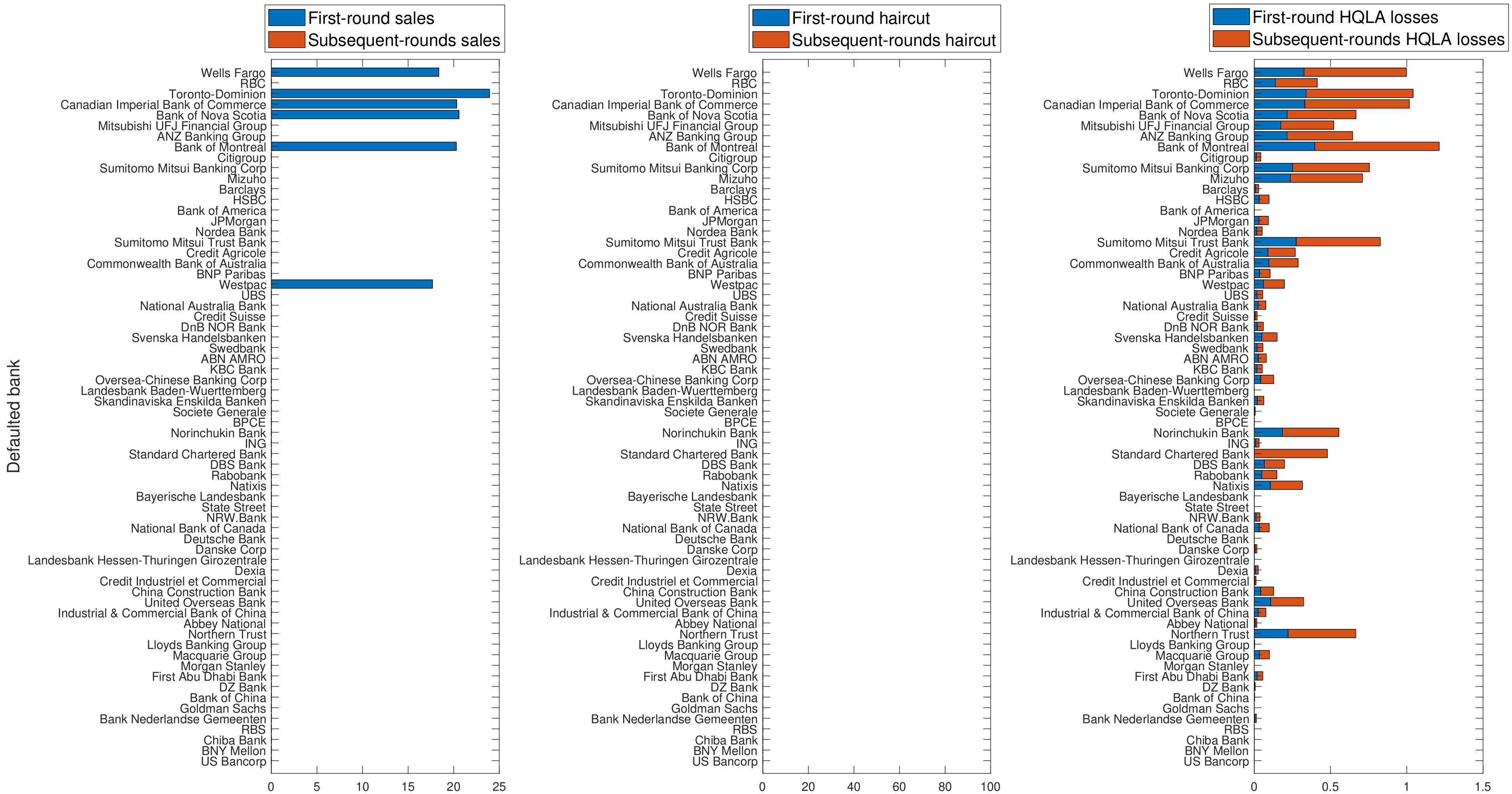

(a) Asset sales of all MMFs ($m)

(b) Haircut (%)

(c) HQLA losses of all other banks ($bn)

Figure C.3: Summary of results 2 (counterparty risk)

Subfigure (a) presents the total asset sales by MMFs to satisfy redemptions after the default of each corresponding bank. Subfigure (b) presents the average haircut applied by banks to asset sales by MMFs after the default of each corresponding bank. Subfigure (c) presents the total HQLA losses of banks due to the support offered to CNAV MMFs (first round) and the funding shortfall as well as any subsequent support and purchases of MMF assets (subsequent rounds).

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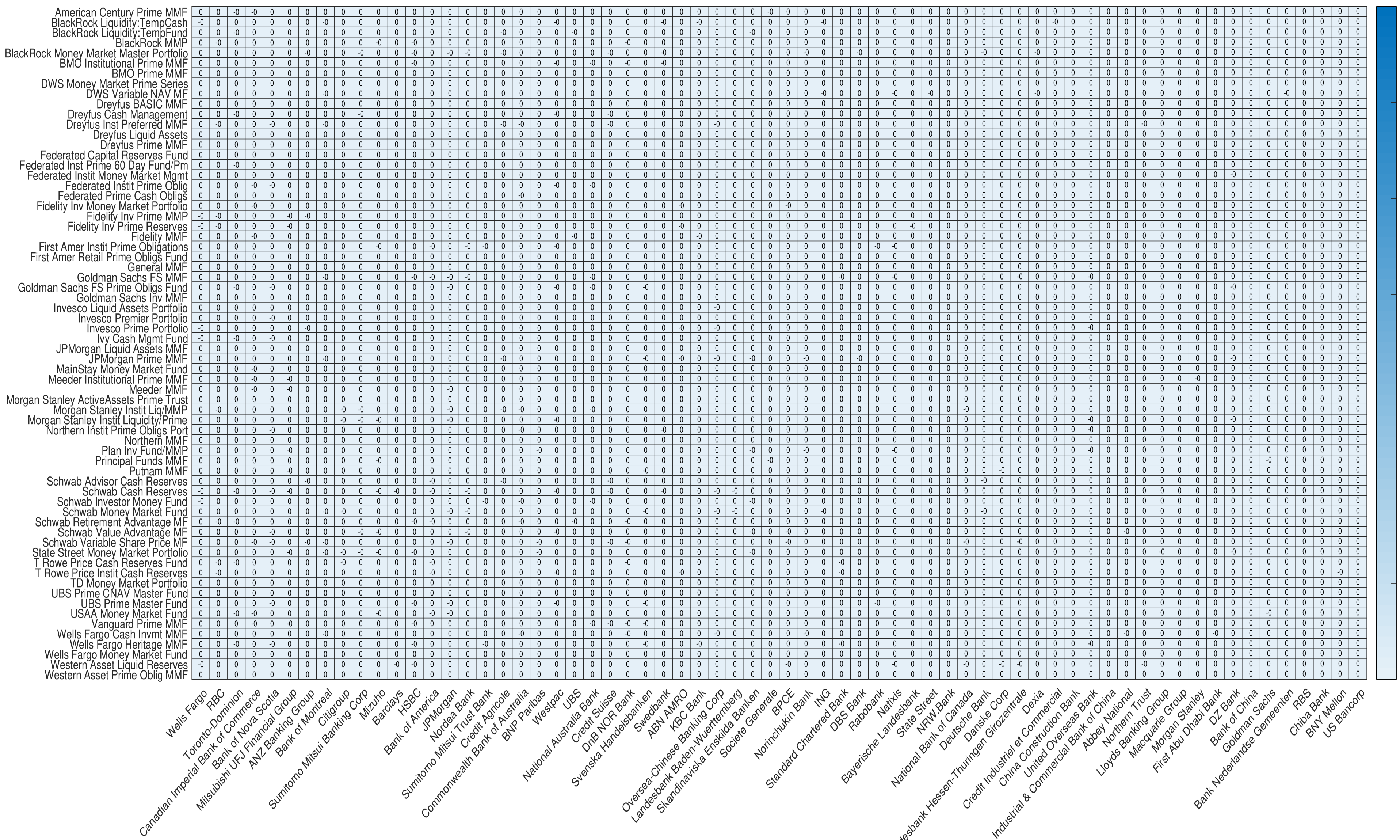

Figure C.4: Subsequent-rounds MMF returns (counterparty risk)

This figure presents the subsequent-rounds negative MMF returns in % due to fire sales losses as a result of subsequent redemptions.

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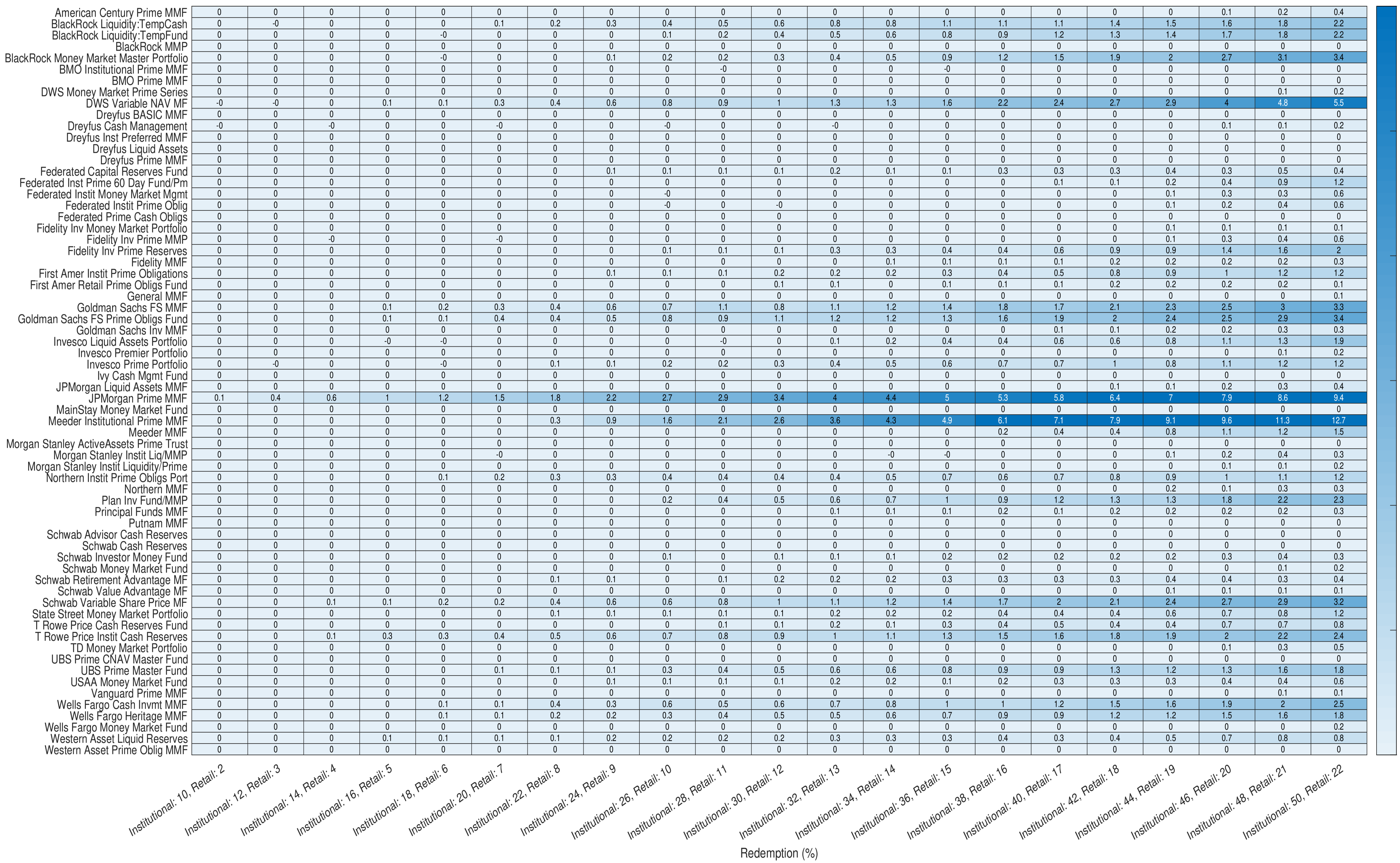

Figure C.5: First-round MMF returns (liquidity risk)

This figure presents the first-round negative MMF returns in % due to fire sales losses as a result of the exogenous redemption shock.

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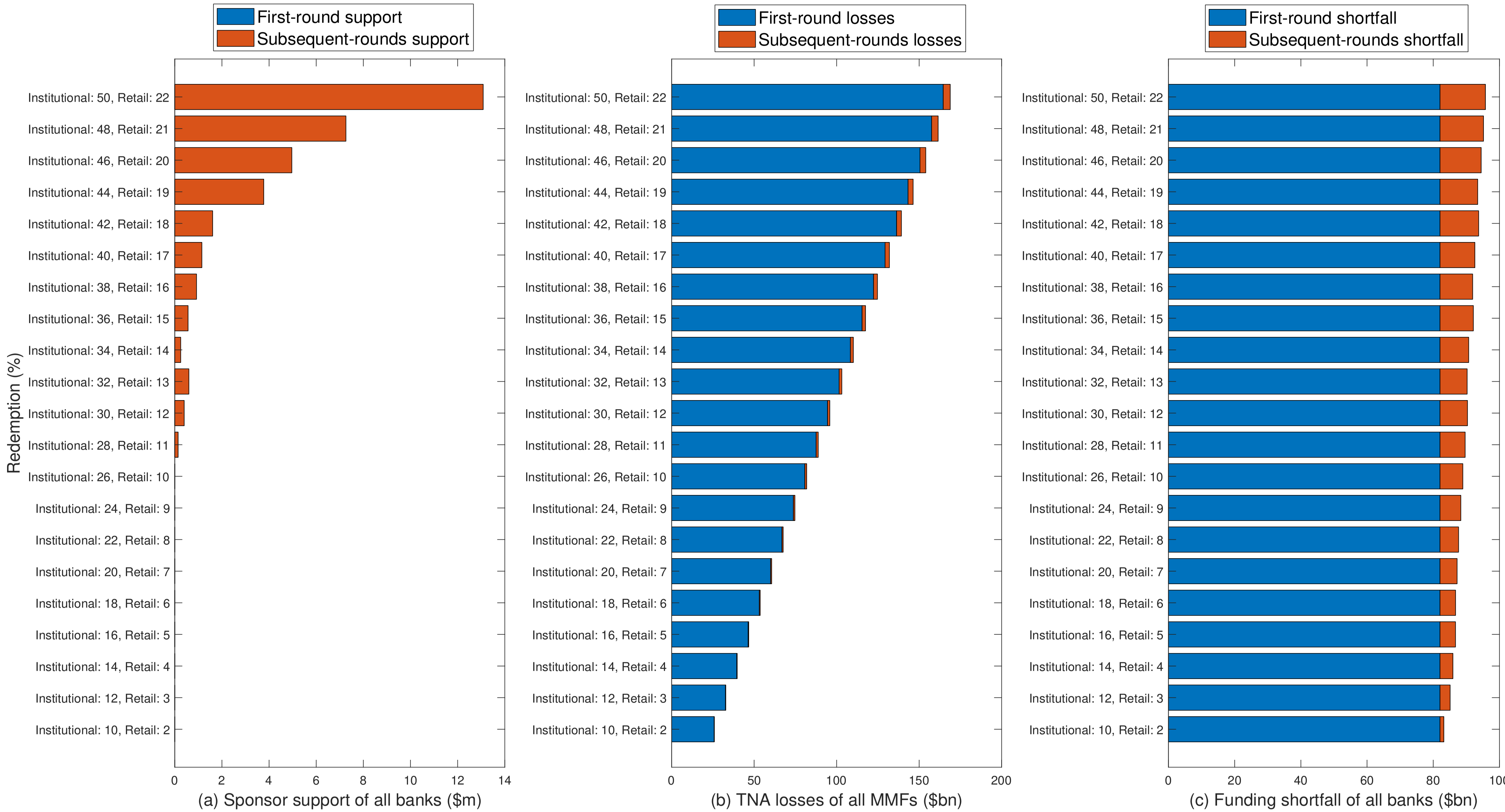

Figure C.6: Summary of results 1 (liquidity risk)

Subfigure (a) presents the total sponsor support offered by banks to CNAV MMFs in danger of breaking the buck as a result of fire sales losses. Subfigure (b) presents the total MMF TNA losses due to the exogenous redemption shock (first round) and due to secondary redemptions (subsequent rounds). Subfigure (c) presents the total funding shortfall of banks following the withdrawal of funding by MMFs facing redemptions.

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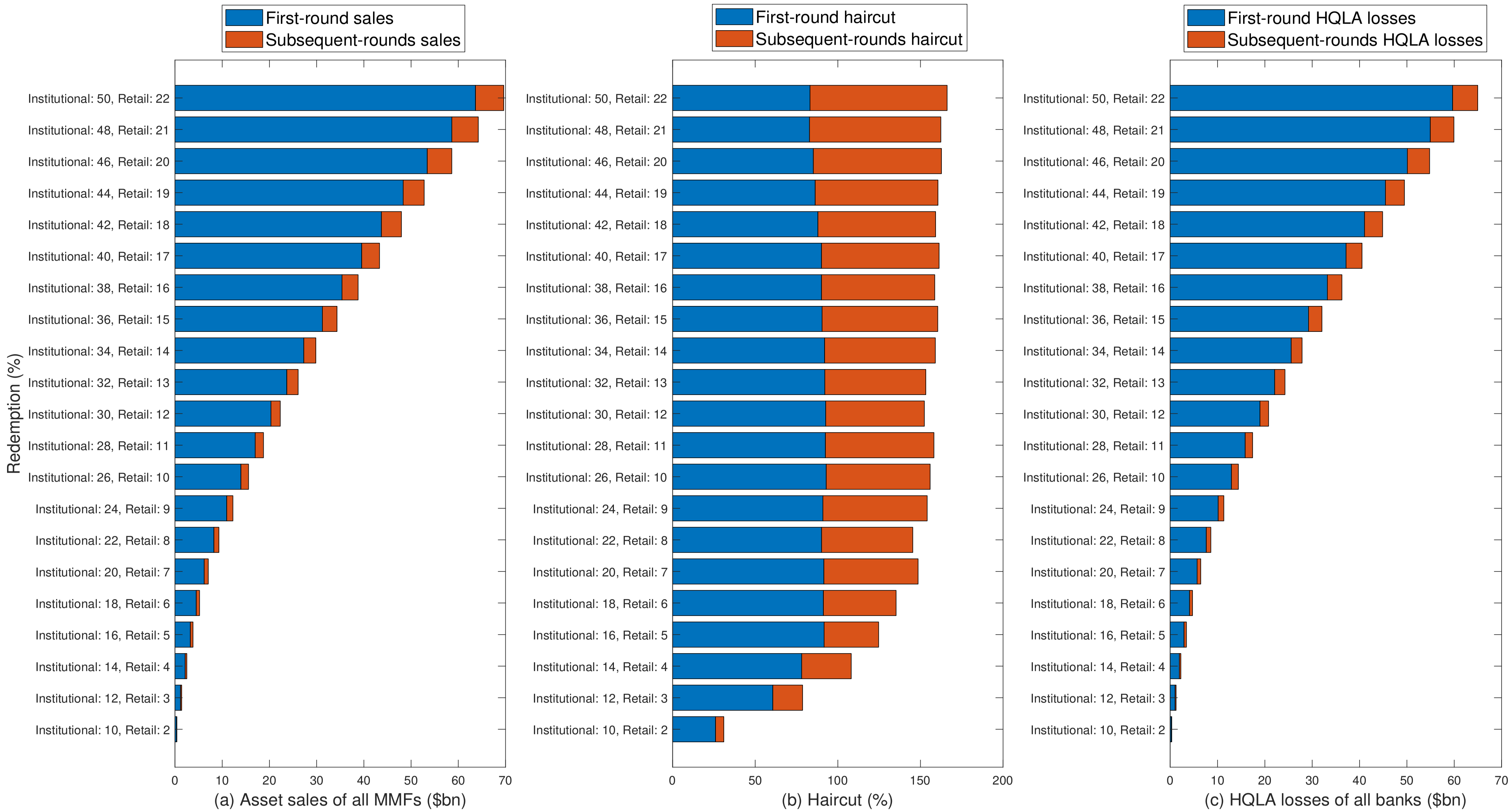

Figure C.7: Summary of results 2 (liquidity risk)

Subfigure (a) presents the total asset sales by MMFs to satisfy redemptions. Subfigure (b) presents the average haircut applied by banks to asset sales by MMFs due to the redemptions. Subfigure (c) presents the total HQLA losses of banks due to the funding shortfall as well as any subsequent support and purchases of MMF assets.

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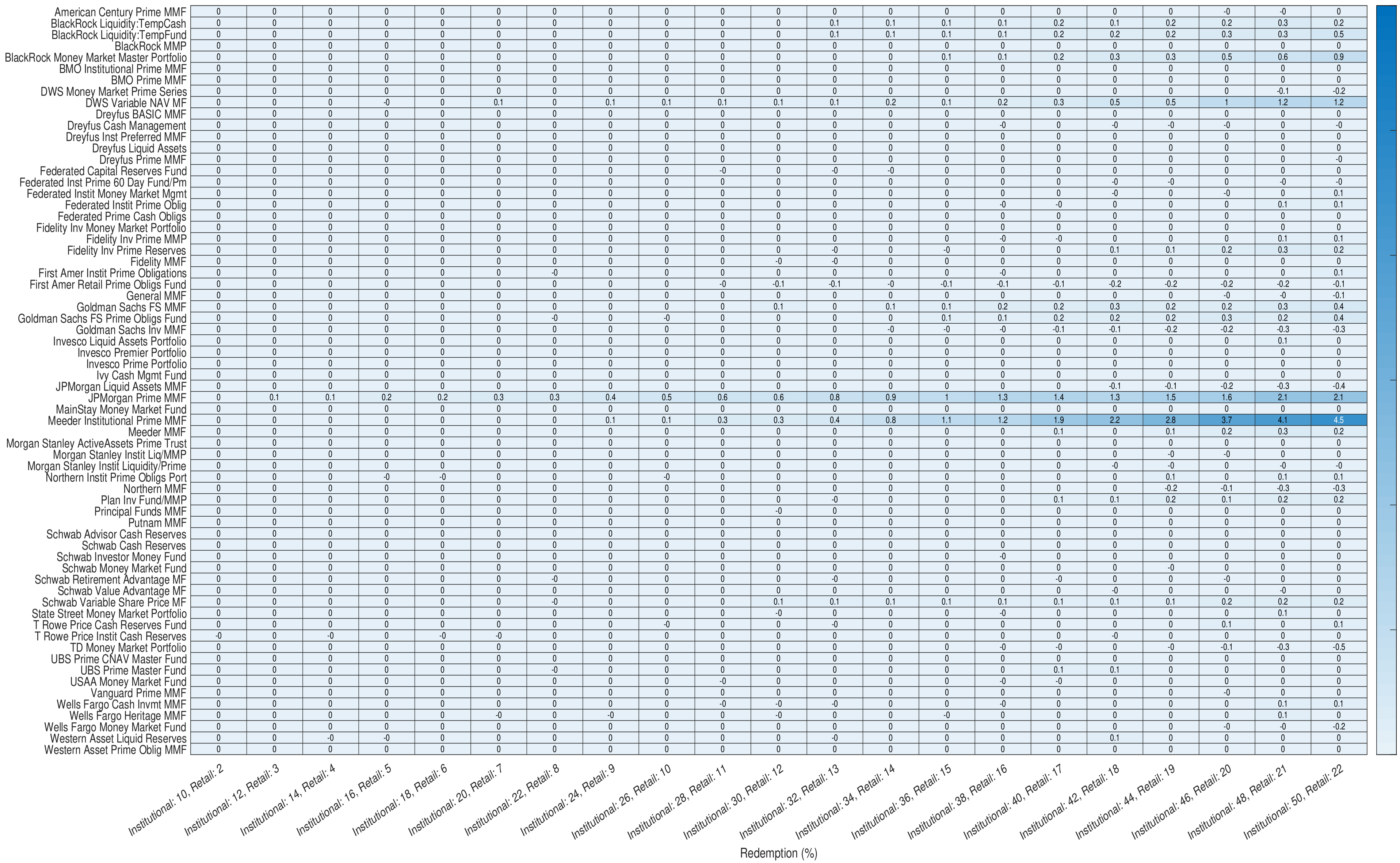

Figure C.8: Subsequent-rounds MMF returns (liquidity risk)

This figure presents the subsequent-rounds negative MMF returns in % due to fire sales losses as a result of subsequent redemptions.

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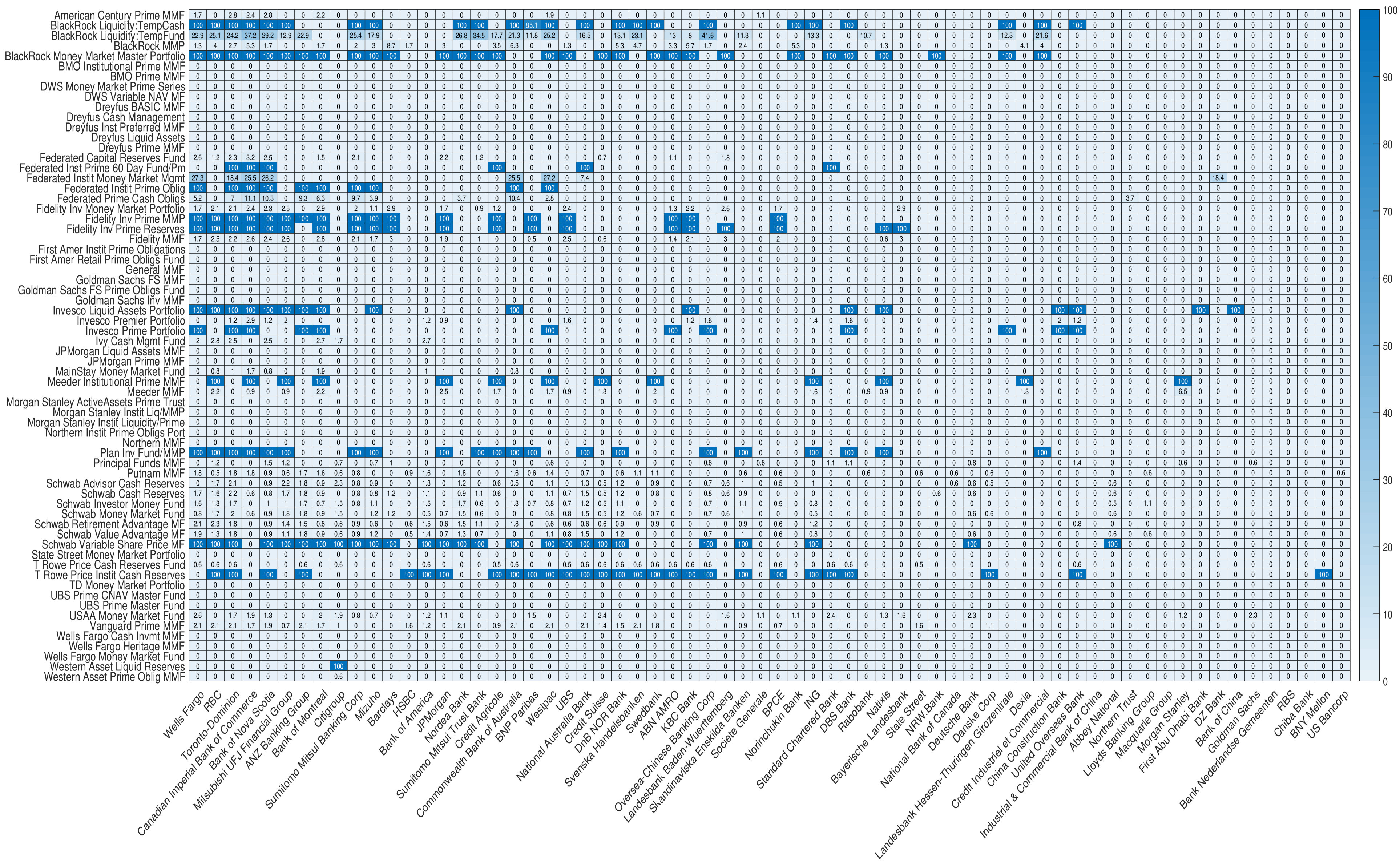

Figure C.9: First-round MMF returns (no MMF regulations)

This figure presents the first-round negative MMF returns in % due to asset losses and resulting redemptions after the default of each corresponding bank.

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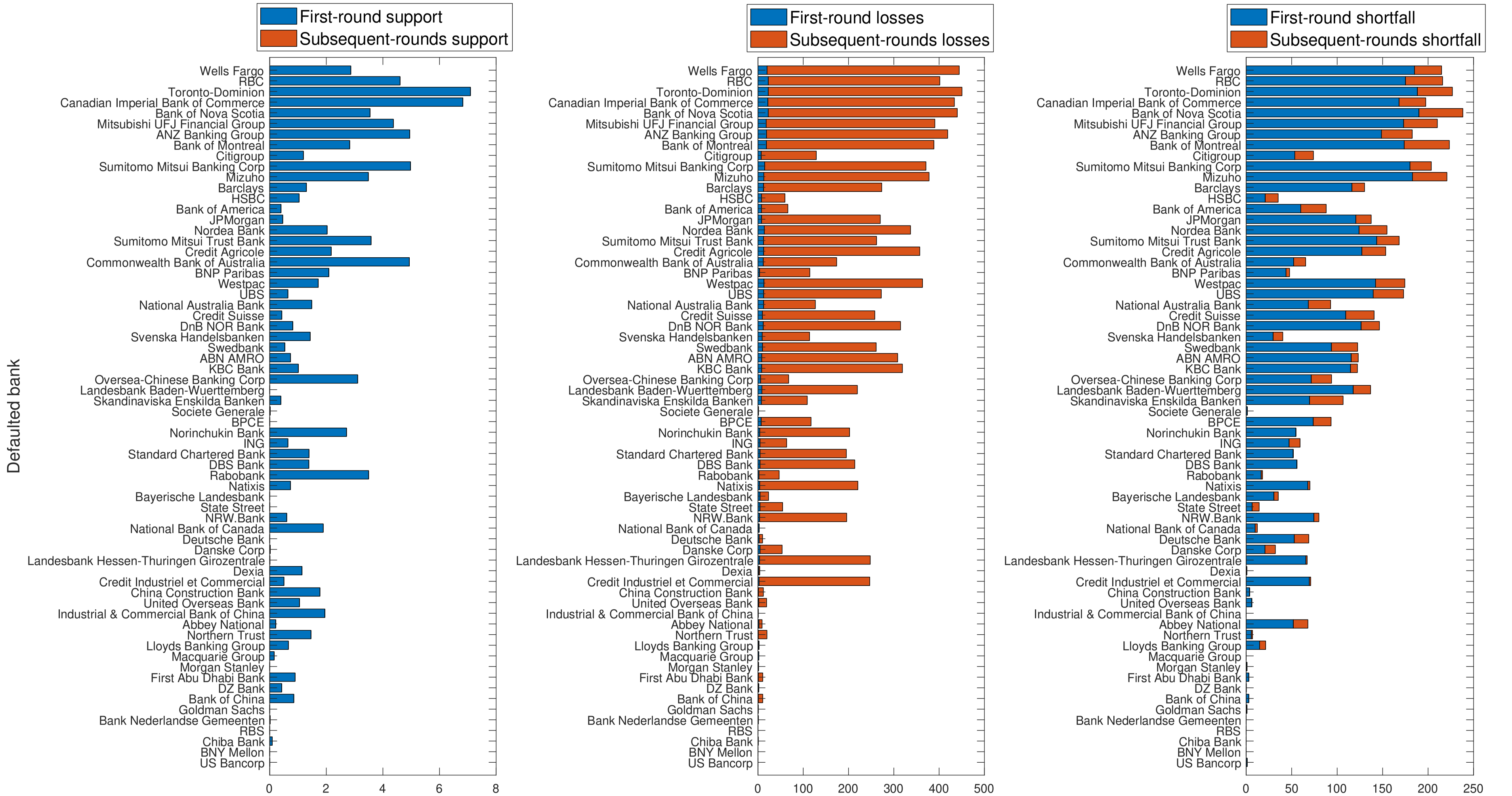

(a) Sponsor support of all other banks ($bn)

(b) TNA losses of all MMFs ($bn)

(c) Funding shortfall of all other banks ($bn)

Figure C.10: Summary of results 1 (no MMF regulations)

Subfigure (a) presents the total sponsor support offered by banks to CNAV MMFs in danger of breaking the buck after the default of each corresponding bank. Subfigure (b) presents the total MMF TNA losses due to assets' devaluation after the default of each corresponding bank (first round) and due to secondary redemptions (subsequent rounds). Subfigure (c) presents the total funding shortfall of banks following the withdrawal of funding by MMFs facing redemptions after the default of each corresponding bank.

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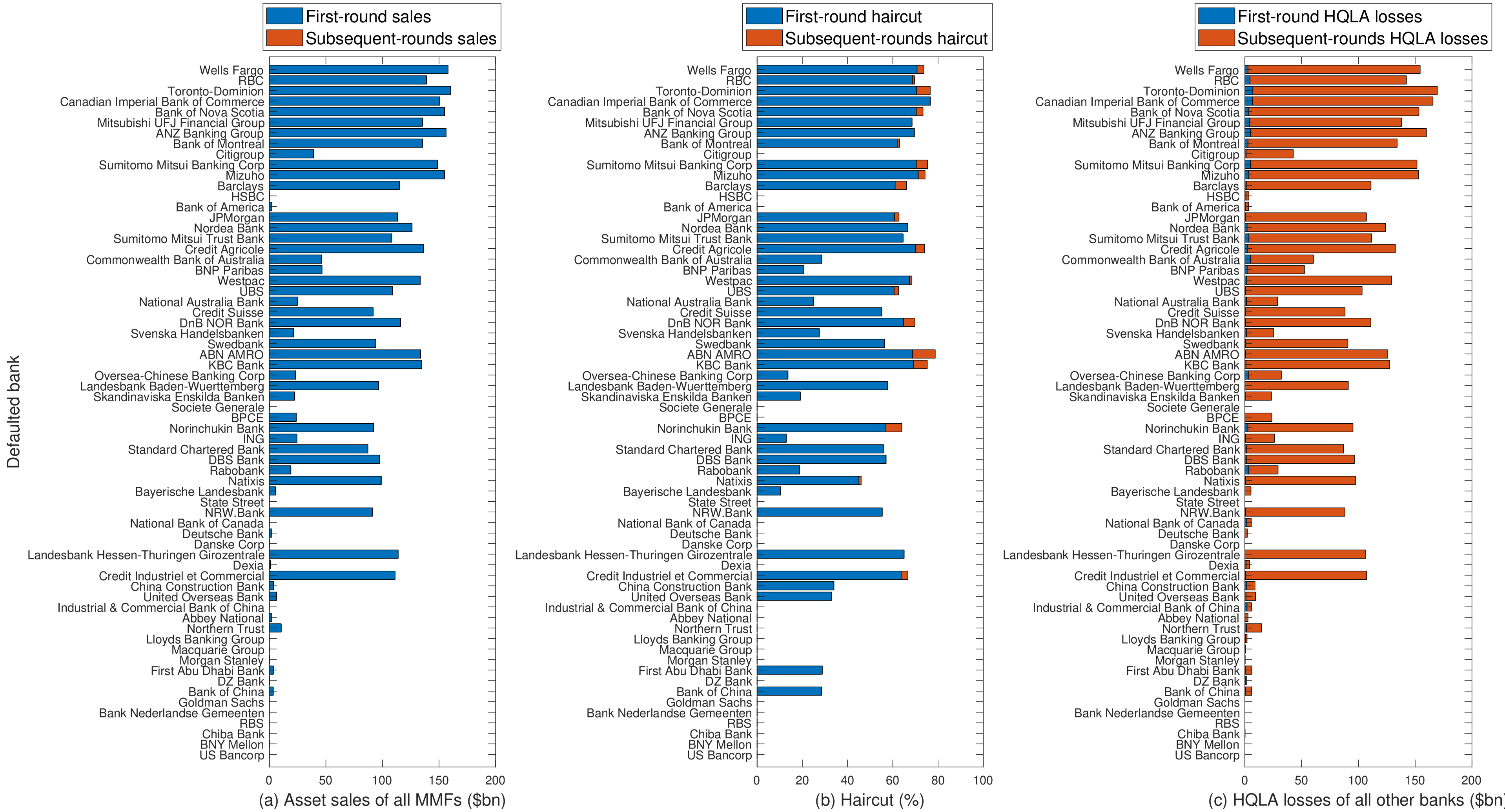

Figure C.11: Summary of results 2 (no MMF regulations)

Subfigure (a) presents the total asset sales by MMFs to satisfy redemptions after the default of each corresponding bank. Subfigure (b) presents the average haircut applied by banks to asset sales by MMFs after the default of each corresponding bank. Subfigure (c) presents the total HQLA losses of banks due to the support offered to CNAV MMFs (first round) and the funding shortfall as well as any subsequent support and purchases of MMF assets (subsequent rounds).

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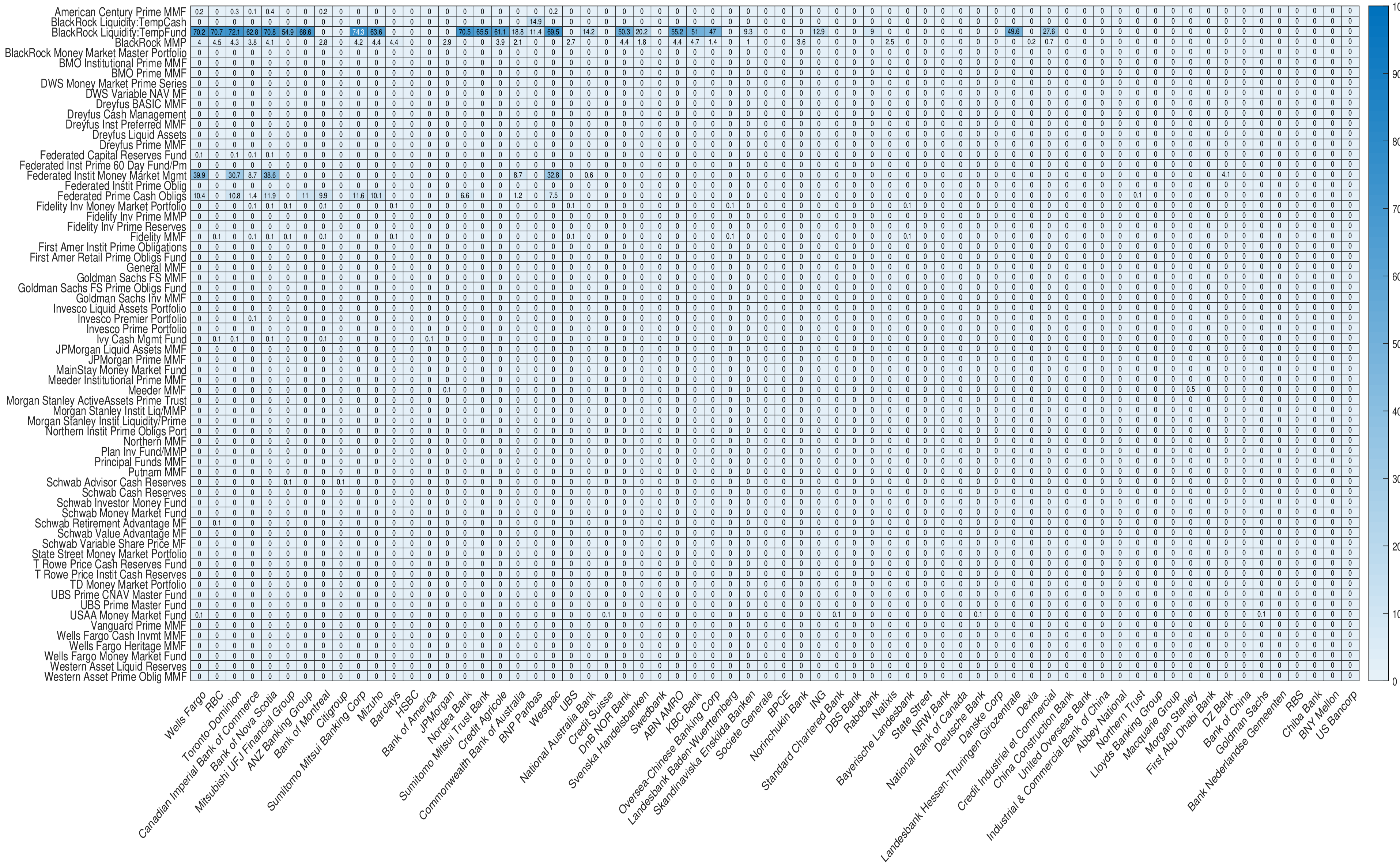

Figure C.12: Subsequent-rounds MMF returns (no MMF regulations)

This figure presents the subsequent-rounds negative MMF returns in % due to fire sales losses as a result of subsequent redemptions.

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Chapter 5

Conclusion

The introduction of regulations aimed at mitigating systemic risk following the financial crisis has transformed the financial system. Many of the vulnerabilities that manifested have been addressed by enhancing the resilience of the banking and shadow banking sectors. Yet, as the recent market turbulence in March 2020 due to Covid-19 demonstrated, new vulnerabilities have arisen which have showcased the need for an understanding of the new channels of stress in the financial system in order to mitigate them.

This thesis has contributed to this understanding by examining various sectors of the financial system that have received academic and regulatory focus over the past decade. The first essay examined the effects of the mandatory collateralisation of OTC derivatives contracts that are not centrally cleared through CCPs on counterparty, liquidity and systemic risks. Using a stress-testing network model calibrated to balance sheet data of the largest dealer banks in the OTC derivatives markets, the findings indicate that the regulation is successful in reducing counterparty and systemic risks, at the expense of higher liquidity risk and increased fragility of CCPs. When the financial system is hit by large shocks, this can give rise to a dash-for-cash as market participants try to raise cash to pay their obligations. Hence, our results contribute to the academic literature on derivatives clearing by showcasing the trade-offs between the various forms of risk and their systemic implications, as well as to the current policy debate on the role of margining practices in amplifying funding strains.

The second essay examined the mechanism through which ETFs can affect the prices, liquidity and volatility of the underlying equities and corporate debt securities. Using a proprietary dataset of the Central Bank of Ireland containing all Irish ETFs and their holdings, the findings suggest that ETFs have a strong effect on equities' liquidity and prices and increase their volatility, but only have a weak or insignificant effect on corporate debt securities' liquidity and prices and decrease their volatility. By examining both underlying asset classes jointly we are able to propose a mechanism that explains these differential effects by relying on the theoretical framework that looks at information links between assets. Our results thus contribute to the academic literature that has examined such effects separately on each underlying asset class, as well as to the policy debate on whether ETFs can propagate shocks to the underlying securities.

The third essay examined the potential of MMFs to act as a source of systemic liquidity risk and the resilience of the banking sector against this risk. Using a stress-testing network model calibrated to the US MMF holdings data, the findings suggest that the banks can withstand liquidity shocks arising from a withdrawal of short-term funding from MMFs due to their high liquidity reserves. However, the MMFs, while more resilient to redemption shocks following the post-crisis regulations, can still face severe fire sales losses if the banks are unwilling to buy back commercial paper and market liquidity evaporates. The results thus highlight the continual vulnerability of MMFs and contribute to the academic literature on MMFs which has mainly focused on the financial crisis period. The results are also consistent with the MMF stress observed in the recent market turmoil in March 2020, and highlight the need for reform of the market structure of commercial paper in order to ensure that it remains liquid even during times of stress.

The findings of the thesis provide multiple avenues for future research. On OTC derivatives markets, it would be interesting to examine how different market participants react to liquidity shocks and whether margin procyclicality causes excessive strain on them. On ETFs, future research can examine the effects of information links further to discover new ways of shock propagation to the underlying securities. Finally, on MMFs it would be interesting to examine the optimal market structure of the securities they invest in that would make them more resilient and limit their role as propagators of systemic liquidity risk.

Bibliography

Abruzzo, N. and Park, Y.-H. (2016). An empirical analysis of futures margin changes: determinants and policy implications. *Journal of Financial Services Research*, 49(1):65–100.

Acharya, V. V. (2009). A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability*, 5(3):224–255.

Acharya, V. V. and Bisin, A. (2014). Counterparty risk externality: Centralized versus over-the-counter markets. *Journal of Economic Theory*, 149:153–182.

Acharya, V. V. and Merrouche, O. (2013). Precautionary Hoarding of Liquidity and Interbank Markets: Evidence from the Subprime Crisis. *Review of Finance*, 17(1):107–160.

Acharya, V. V. and Mora, N. (2015). A Crisis of Banks as Liquidity Providers. *Journal of Finance*, 70(1):1–43.

Acharya, V. V., Pedersen, L. H., Philippon, T., and Richardson, M. (2017). Measuring systemic risk. *Review of Financial Studies*, 30(1):2–47.

Acharya, V. V., Schnabl, P., and Suarez, G. (2013). Securitization without risk transfer. *Journal of Financial Economics*, 107(3):515–536.

Acharya, V. V. and Steffen, S. (2020). The Risk of Being a Fallen Angel and the Corporate

Dash for Cash in the Midst of COVID. NBER Working Paper No. 27601, National Bureau of Economic Research.

Acharya, V. V. and Yorulmazer, T. (2008). Cash-in-the-market pricing and optimal resolution of bank failures. *Review of Financial Studies*, 21(6):2705–2742.

Adrian, T. (2017). Shadow Banking and Market Based Finance. International Monetary Fund Speech.

Adrian, T. and Brunnermeier, M. K. (2016). CoVaR. *American Economic Review*, 106(7):1705–41.

Agapova, A. and Volkov, N. (2018). ETFs and Price Volatility of Underlying Bonds. Working paper, Florida Atlantic University.

Agarwal, V., Hanouna, P., Moussawi, R., and Stahel, C. W. (2017). Do ETFs Increase the Commonality in Liquidity of Underlying Stocks? Working paper, Villanova University.

Aldasoro, I. and Faia, E. (2016). Systemic loops and liquidity regulation. *Journal of Financial Stability*, 27:1–16.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, 5(1):31–56.

Amini, H., Filipović, D., and Minca, A. (2015). Systemic risk and central clearing counterparty design. Swiss Finance Institute Research Paper No. 13-34.

Anand, A., Irvine, P., Puckett, A., and Venkataraman, K. (2013). Institutional trading and stock resiliency: Evidence from the 2007–2009 financial crisis. *Journal of Financial Economics*, 108(3):773–797.

Aramonte, S. and Avalos, F. (2020). The recent distress in corporate bond markets: cues from ETFs. BIS Bulletin No. 6, Bank for International Settlements.

Ashcraft, A., McAndrews, J., and Skeie, D. (2011). Precautionary Reserves and the Interbank Market. *Journal of Money, Credit and Banking*, 43:311–348.

Bae, K. and Kim, D. (2020). Liquidity risk and exchange-traded fund returns, variances, and tracking errors. *Journal of Financial Economics*, 138(1):222–253.

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.

Baranova, Y., Coen, J., Lowe, P., Noss, J., and Silvestri, L. (2017). Simulating stress across the financial system: the resilience of corporate bond markets and the role of investment funds. Financial Stability Paper No. 42, Bank of England.

BCBS (2015). Identification and measurement of step-in risk. Basel Committee on Banking Supervision.

BCBS-IOSCO (2015). Margin requirements for non-centrally cleared derivatives. Basel Committee on Banking Supervision and International Organization of Securities Commissions.

Bellia, M., Panzica, R., Pelizzon, L., and Peltonen, T. (2017). The demand for central clearing: to clear or not to clear, that is the question. ESRB Working Paper Series No. 62, European Systemic Risk Board.

Ben-David, I., Franzoni, F., and Moussawi, R. (2018). Do ETFs Increase Volatility? *Journal of Finance*, 73(6):2471–2535.

Berndsen, R. (2020). Five Fundamental Questions on Central Counterparties. CentER Discussion Paper No. 2020-028, Center for Economic Research.

Bessembinder, H., Jacobsen, S., Maxwell, W., and Venkataraman, K. (2018). Capital Commitment and Illiquidity in Corporate Bonds. *Journal of Finance*, 73(4):1615–1661.

Bhattacharya, A. and O'Hara, M. (2018). Can ETFs Increase Market Fragility? Effect of Information Linkages in ETF Markets. Working paper, Cornell University.

Bhattacharya, A. and O'Hara, M. (2020). ETFs and Systemic Risks. CFA Institute Research Foundation, Brief.

Biais, B., Heider, F., and Hoerova, M. (2012). Clearing, counterparty risk, and aggregate risk. *IMF Economic Review*, 60(2):193–222.

Bignon, V. and Vuillemey, G. (2018). The failure of a clearinghouse: Empirical evidence. *Review of Finance*, pages 1–30.

BIS (2017). OTC derivatives statistics at end-December 2016. Bank for International Settlements.

BIS (2019). OTC derivatives statistics at end-December 2018. Bank for International Settlements.

BoE (2015). The Bank of England's approach to stress testing the UK banking system. Bank of England.

BoE (2020a). Financial Stability Report August 2020. Bank of England.

BoE (2020b). Interim Financial Stability Report May 2020. Bank of England.

Bonner, C., Wedow, M., Budnik, K., Koban, A., Kok, C., Laliotis, D., Meller, B., Melo, A., Moldovan, I., Schmitz, S., and Couaillier, C. (2018). Systemic liquidity concept, measurement and macroprudential instruments. Occasional Paper Series No. 214, European Central Bank.

Brady, S. A., Anadu, K. E., and Cooper, N. R. (2012). The Stability of Prime Money Market Mutual Funds: Sponsor Support from 2007 to 2011. Federal Reserve Bank of Boston, Risk and Policy Analysis Working Papers, RPA 12(3).

Brunnermeier, M. and Cheridito, P. (2019). Measuring and allocating systemic risk. *Risks*, 7(2).

Brunnermeier, M. K. and Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial Studies*, 22(6):2201–2238.

Cenedese, G., Ranaldo, A., and Vasios, M. (2020). OTC premia. *Journal of Financial Economics*, 136(1):86–105.

Cespa, G. and Foucault, T. (2014). Illiquidity Contagion and Liquidity Crashes. *Review of Financial Studies*, 27(6):1615–1660.

CFTC (2019). CCP Supervisory Stress Tests: Reverse Stress Test and Liquidation Stress Test. Commodity Futures Trading Commission.

CFTC-SEC (2010). Findings regarding the market events of May 6, 2010. Commodity Futures Trading Commission and Securities and Exchange Commission.

Che, Y.-K. and Gale, I. (1998). Standard auctions with financially constrained bidders. *Review of Economic Studies*, 65(1):1–21.

Chen, Q., Goldstein, I., and Jiang, W. (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics*, 97(2):239–262.

Chernenko, S. and Sunderam, A. (2014). Frictions in Shadow Banking: Evidence from the Lending Behavior of Money Market Mutual Funds. *Review of Financial Studies*, 27(6):1717–1750.

Cipriani, M., Martin, A., McCabe, P., and Parigi, B. M. (2014). Gates, Fees, and Preemptive Runs. Federal Reserve Bank of New York Staff Report No. 670.

Cont, R. (2017). Central clearing and risk transformation. Financial Stability Review 21, Banque de France.

Cont, R. and Schaanning, E. (2016). Fire Sales, Indirect Contagion and Systemic Stress Testing. Available at SSRN 2541114.

Cornett, M. M., McNutt, J. J., Strahan, P. E., and Tehranian, H. (2011). Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics*, 101(2):297–312.

Cox, R. T. (2015). Central counterparties in crisis: The Hong Kong Futures Exchange in the crash of 1987. *Journal of Financial Market Infrastructures*, 4(2):73–98.

CPSS-IOSCO (2012). Principles for financial market infrastructures. Committee on Payment and Settlement Systems and International Organization of Securities Commissions.

Craig, B. and Von Peter, G. (2014). Interbank tiering and money center banks. *Journal of Financial Intermediation*, 23(3):322–347.

Cunliffe, J. (2020). Financial System Resilience: Lessons from a real stress. Bank of England Speech, Investment Association Webinar.

Da, Z. and Shive, S. (2015). When the bellwether dances to noise : Evidence from exchange-traded funds. Working paper, Notre Dame University.

Dannhauser, C. D. (2017). The impact of innovation: Evidence from corporate bond exchange-traded funds (ETFs). *Journal of Financial Economics*, 125(3):537–560.

Demekas, D. G. (2015). Designing effective macroprudential stress tests: Progress so far and the way forward. IMF Working Paper 15/146, International Monetary Fund.

Diamond, D. W. and Dybvig, P. H. (1983). Bank Runs, Deposit Insurance, and Liquidity. *Journal of Political Economy*, 91(3):401–419.

Dimitrov, V., Palia, D., and Tang, L. (2015). Impact of the Dodd-Frank act on credit ratings. *Journal of Financial Economics*, 115(3):471–492.

Domanski, D., Gambacorta, L., and Picillo, C. (2015). Central clearing: trends and current issues. BIS Quarterly Review, Bank for International Settlements.

Duffie, D., Malamud, S., and Manso, G. (2014). Information percolation in segmented markets. *Journal of Economic Theory*, 153:1–32.

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

Duffie, D. and Zhu, H. (2011). Does a central clearing counterparty reduce counterparty risk? *Review of Asset Pricing Studies*, 1(1):74–95.

Duygan-Bump, B., Parkinson, P., Rosengren, E., Suarez, G. A., and Willen, P. (2013). How Effective Were the Federal Reserve Emergency Liquidity Facilities? Evidence from the

Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility. *Journal of Finance*, 68(2):715–737.

ESMA (2018). EU-wide CCP Stress Test 2017. European Securities and Markets Authority.

ESRB (2020). Issues note on liquidity in the corporate bond and commercial paper markets, the procyclical impact of downgrades and implications for asset managers and insurers. European Systemic Risk Board.

ETFGI (2020). ETFGI reports assets invested in ETFs and ETPs listed globally broke through the $7 trillion milestone at the end of August 2020. Retrieved from: `https://etfgi.com/news/press-releases/2020/09/etfgi-reports-assets-invested-etfs-and-etps-listed-globally-broke`.

Evans, R. B., Moussawi, R., Pagano, M. S., and Sedunov, J. (2017). ETF Short Interest and Failures-to-Deliver: Naked Short-Selling or Operational Shorting? Working paper, Darden Business School.

Farhi, E. and Tirole, J. (2012). Collective Moral Hazard, Maturity Mismatch, and Systemic Bailouts. *American Economic Review*, 102(1):60–93.

FCA (2016). Market-Based Finance: Its Contributions and Emerging Issues. Financial Conduct Authority.

Ferrara, G., Langfield, S., Liu, Z., and Ota, T. (2019). Systemic illiquidity in the interbank network. *Quantitative Finance*, 19(11):1779–1795.

Ferrara, G., Li, X., and Marszalec, D. (2017). Central counterparty auction design. Bank of England Staff Working Paper No. 669.

FIA (2020). Revisiting Procyclicality: The Impact of the COVID Crisis on CCP Margin Requirements. Futures Industry Association.

FSB (2020a). Global Monitoring Report on Non-Bank Financial Intermediation. Financial Stability Board.

FSB (2020b). Holistic Review of the March Market Turmoil. Financial Stability Board.

G20 (2009). G20 leaders statement: The Pittsburgh Summit.

G20 (2011). G20 leaders statement: The Cannes Summit.

Gallagher, E. A., Schmidt, L. D. W., Timmermann, A., and Wermers, R. (2020). Investor Information Acquisition and Money Market Fund Risk Rebalancing during the 2011–2012 Eurozone Crisis. *Review of Financial Studies*, 33(4):1445–1483.

Ghamami, S. and Glasserman, P. (2017). Does OTC derivatives reform incentivize central clearing? *Journal of Financial Intermediation*, 32:76–87.

Gilboa, I. and Schmeidler, D. (1989). Maximin expected utility with non-unique prior. *Journal of Mathematical Economics*, pages 141–153.

Glasserman, P., Moallemi, C. C., and Yuan, K. (2016). Hidden illiquidity with multiple central counterparties. *Operations Research*, 64(5):1143–1158.

Glosten, L., Nallareddy, S., and Zou, Y. (2020). ETF Activity and Informational Efficiency of Underlying Securities. *Management Science*, pages 1–26.

Goldstein, I., Jiang, H., and Ng, D. T. (2017). Investor flows and fragility in corporate bond funds. *Journal of Financial Economics*, 126(3):592–613.

Gorton, G. and Metrick, A. (2012). Securitized banking and the run on repo. *Journal of Financial Economics*, 104(3):425–451.

Gregory, J. (2014). *Central Counterparties: Mandatory Central Clearing and Initial Margin Requirements for OTC Derivatives*. John Wiley & Sons.

Grossman, S. J. (1989). An analysis of the implications for stock and futures price volatility of program trading and dynamic hedging strategies. NBER Working paper No. 2357, National Bureau of Economic Research.

Hałaj, G. and Kok, C. (2015). Modelling the emergence of the interbank networks. *Quantitative Finance*, 15(4):653–671.

Heath, A., Kelly, G., Manning, M., Markose, S., and Shaghaghi, A. R. (2016). CCPs and network stability in OTC derivatives markets. *Journal of Financial Stability*, 27:217–233.

Hu, G. X., Pan, J., and Wang, J. (2013). Noise as Information for Illiquidity. *Journal of Finance*, 68(6):2341–2382.

Huang, W. and Takáts, E. (2020). The CCP-bank nexus in the time of Covid-19. BIS Bulletin No. 13, Bank for International Settlements.

Hull, J. C. (2018). *Options, futures, and other derivatives*. Pearson, New York, 10th edition.

ICEU (2017). ICE Clear Europe Clearing Rules. Retrieved from: `https://www.theice.com/publicdocs/clear_europe/rulebooks/rules/Clearing_Rules.pdf`.

ICI (2016). 2016 Investment Company Factbook: A Review of Trends and Activities in the Investment Company Industry, 56th edition. Investment Company Institute.

ICI (2018). 2018 Investment Company Factbook: A Review of Trends and Activities in the Investment Company Industry, 58th edition. Investment Company Institute.

IMF (2010). Global Financial Stability Report: Sovereigns, Funding, and Systemic Liquidity. International Monetary Fund.

IMF (2011). Global Financial Stability Report: Durable Financial Stability, Getting There from Here. International Monetary Fund.

ISDA (2014a). Dispelling Myths: End-User Activity in OTC Derivatives. International Swaps and Derivatives Association.

ISDA (2014b). ISDA Margin Survey 2014. International Swaps and Derivatives Association.

ISDA (2015). CCP default management, recovery and continuity: A proposed recovery framework. International Swaps and Derivatives Association.

Ivashina, V. and Scharfstein, D. S. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, 97(3):319–338.

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

King, M. A. and Wadhwani, S. (1990). Transmission of Volatility between Stock Markets. *Review of Financial Studies*, 3(1):5–33.

King, T. B., Nesmith, T. D., Paulson, A. L., and Prono, T. (2020). Central clearing and systemic liquidity risk. FEDS Working Paper, Federal Reserve Board.

Lenkey, S. and Song, F. (2016). Redemption Fees and Information-Based Runs. Working paper, Pennsylvania State University.

Lewandowska, O. and Glaser, F. (2017). The recent crises and central counterparty risk practices in the light of procyclicality: empirical evidence. *Journal of Financial Market Infrastructures*, 5(3):1–24.

Li, L., Li, Y., Macchiavelli, M., and Zhou, X. (2020). Runs and Interventions in the Time of Covid-19: Evidence from Money Funds. Available at SSRN 3607593.

Loon, Y. C. and Zhong, Z. K. (2014). The impact of central clearing on counterparty risk, liquidity, and trading: Evidence from the credit default swap market. *Journal of Financial Economics*, 112(1):91–115.

MAGD (2013). Macroeconomic impact assessment of OTC derivatives regulatory reforms. Macroeconomic Assessment Group on Derivatives, Bank for International Settlements.

Markose, S. (2012). Systemic risk from global financial derivatives: A network analysis of contagion and its mitigation with super-spreader tax. IMF Working Paper 12/282, International Monetary Fund.

McPartland, J. and Lewis, R. (2016). The challenges of derivatives central counterparty interoperability arrangements. *Journal of Financial Market Infrastructures*, 4(4):41–51.

Meisser, L. and Kreuser, C. F. (2017). An Agent-Based Simulation of the Stolper–Samuelson Effect. *Computational Economics*, 50(4):533–547.

Menkveld, A. J. (2016). Systemic risk in central clearing: Should crowded trades be avoided? Working paper, VU Amsterdam.

Milgrom, P. R. and Weber, R. J. (1982). A theory of auctions and competitive bidding. *Econometrica*, 50(5):1089–1122.

Mägerle, J. and Nellen, T. (2015). Interoperability between central counterparties. *Journal of Financial Market Infrastructures*, 4(2):49–71.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108(1):1–28.

Paddrik, M., Rajan, S., and Young, H. P. (2020). Contagion in Derivatives Markets. *Management Science*, pages 1–14.

Pan, K. and Zeng, Y. (2017). ETF Arbitrage under Liquidity Mismatch. Working paper, Harvard University.

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

Pedersen, L. H. (2009). When everyone runs for the exit. *International Journal of Central Banking*, 5(4):177–199.

Pirrong, C. (2014). A bill of goods: central counterparties and systemic risk. *Journal of Financial Market Infrastructures*, 2(4):55–85.

Rahi, R. and Zigrand, J.-P. (2009). Strategic Financial Innovation in Segmented Markets. *Review of Financial Studies*, 22(8):2941–2971.

Rochet, J.-C. and Tirole, J. (1996). Interbank lending and systemic risk. *Journal of Money, Credit and Banking*, 28(4):733–762.

Schmidt, L., Timmermann, A., and Wermers, R. (2016). Runs on Money Market Mutual Funds. *American Economic Review*, 106(9):2625–2657.

SEC (2014). SEC Adopts Money Market Fund Reform Rules. Retrieved from: `https://www.sec.gov/news/press-release/2014-143`. Securities and Exchange Commission.

Strahan, P. E. and Tanyeri, B. (2015). Once Burned, Twice Shy: Money Market Fund Responses to a Systemic Liquidity Shock. *Journal of Financial and Quantitative Analysis*, 50(1-2):119–144.

Todorov, K. (2021). The anatomy of bond ETF arbitrage. BIS Quarterly Review, Bank for International Settlements.

Van Horne, J. C. and Wachowicz, J. M. (2008). *Fundamentals of Financial Management*. Financial Times Prentice Hall, Harlow, 13th edition.

Vayanos, D. and Wang, T. (2007). Search and endogenous concentration of liquidity in asset markets. *Journal of Economic Theory*, 136(1):66–104.

Witmer, J. (2016). Does the buck stop here? A comparison of withdrawals from money market mutual funds with floating and constant share prices. *Journal of Banking and Finance*, 66:126–142.