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LIQUIDITY RISK AND FUNDING COST

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Abstract

We propose and test a new channel that links funding liquidity risk and interest rates in short-term funding markets. Unlike existing theories that focus on premiums demanded by lenders, the funding liquidity risk channel postulates that borrowers exposed to liquidity shocks are willing to pay a markup for immediate funding. We test and quantify the channel using unique trade-by-trade data and uncover systematic differences across individual banks' funding cost driven by idiosyncratic liquidity risk. These differences are persistent over a decade, suggesting that the funding liquidity risk channel is relevant in general and not only arises during crisis times.

KEYWORDS: Funding liquidity risk, short-term interest rates, risk premiums, funding cost, interbank market

JEL CODES: G12, G18, G21, E43, E52, D40

1. Introduction

Funding illiquidity arises when solvent but illiquid financial institutions are unable to obtain refinancing. Banks are particularly sensitive to funding illiquidity because maturity transformation—that is, funding long-term assets with short-term liabilities—is at the core of their business model. In classic theories of financial intermediation, funding liquidity risk materializes in the form of bank runs (e.g., Bryant, 1980; Diamond and Dybvig, 1983). The global financial crisis of 2007–2009 re-emphasized the importance of funding liquidity for financial stability and revealed that bank runs can also occur in wholesale funding markets (e.g., Gorton and Metrick, 2012; Perignon, Thesmar, and Vuillemey, 2018).

We propose a new channel that outlines how funding liquidity risk impacts interest rates in short-term funding markets—the funding liquidity risk channel. In extant literature, interest rate or yield spreads are usually attributed to premiums required by lenders as compensation for default risk and market illiquidity.[1] In the funding liquidity risk channel, we turn this rationale upside down. We show that borrowers have a higher willingness to pay for liquidity if they are exposed to liquidity shocks. We test and quantify the channel and reveal systematic heterogeneity across banks' liquidity risk, their willingness to pay for immediate access to liquidity, and hence their funding cost. This heterogeneity is persistent over more than ten years, suggesting that the channel is related to liquidity management in general and not only arises during crisis times.

Figure 1 motivates our novel perspective. It depicts the average overnight funding costs of individual borrowers in the main segment of the euro interbank funding market, the central-

[1] If borrowers are more likely to default or if markets are illiquid, lenders demand higher rates of return. A large body of literature examines these premiums in interbank markets (e.g., Michaud and Upper, 2008; Taylor and Williams, 2009; Filipovic and Trolle, 2013), corporate bond markets (e.g., Longstaff, Mithal, and Neis, 2005; Chen, Lesmond, and Wei, 2007; Friewald, Jankowitsch, and Subrahmanyam, 2012), and sovereign bond markets (e.g. Beber, Brandt, and Kavajecz, 2009; Krishnamurthy and Vissing-Jorgensen, 2012).

counterparty (CCP)-based euro repo market.[2] In this market, lenders cannot ask for risk premiums specific to borrowers because trading is anonymous and centrally cleared. Despite anonymity and central clearing, Panel (a) reveals that there is significant heterogeneity in the average funding costs of individual banks. Some banks pay systematically more than others for their overnight funding. Panel (b) illustrates that these differences are persistent and exhibit considerable time variation on a monthly basis of up to 10 basis points on average in times of crisis; daily spreads between banks with high and low funding cost even reach up to 50 basis points. This is remarkable, given the short maturity of these loans and the fact that the CCP-based repo market is one of the most liquid segments of the euro money market, populated by sophisticated market participants. The magnitude of these interest rate spreads within a single segment of the euro money market is comparable to spreads across different segments in the U.S. money market, which range from 3–5 basis points in calm periods to 20–50 basis points in times of crisis (Duffie and Krishnamurthy, 2016).

[Figure 1 about here.]

We show that it is the exposure of banks to idiosyncratic funding liquidity risk that drives the heterogeneity presented in Panel (a) of Figure 1. In addition, we find that certain banks are systematically and persistently more exposed to funding liquidity risk and that this explains the persistence of the heterogeneity presented in Panel (b). We build a simple model of the funding liquidity risk channel and provide empirical evidence using a unique trade-by-trade data set of funding transactions from 2006 to 2016. In the model, liquidity risk arises from the exposure of banks to liquidity shocks that need to be balanced urgently. In practice, the demand for immediate funding could arise due to, for example, transactions in real-time payment systems, margin calls, or funding that must be obtained until the end of the trading day. Banks differ in their liquidity risk due to the amount of liquidity buffer they have available, their liquidity management capabilities, or

[2] The CCP-based euro repo market is the largest market for euro interbank funding with a quarterly turnover of more than EUR 5.5 trillion (European Central Bank, 2015). A repurchase agreement, short repo, is a contract that stipulates the purchase and repurchase of a security. The repo buyer purchases the asset (mostly fixed-income securities) from the seller and commits to sell it back at a predetermined price in the future. The difference between purchase and repurchase price determines the repo rate. The buyer effectively lends cash to the seller, which makes repos economically identical to collateralized loans. We explain the features of this market in detail in Section 4.

the nature of their business models. Being heavily exposed to time-sensitive liquidity shocks makes it difficult to manage short-term funding in a forward-looking manner. Therefore, banks with high liquidity risk act more aggressively by demanding the immediate execution of their trades. This leads to higher interest rates and, hence, higher funding costs for these banks.

In our empirical analysis, we provide evidence for the funding liquidity risk channel and quantify the markup that borrowers pay due to funding liquidity risk. Three major identification challenges arise: First, we must isolate funding transactions from transactions with other intentions, such as market making, speculation, arbitrage trading, or sourcing a specific security. Second, we must construct a measure for the idiosyncratic funding liquidity risk of borrowers. Finally, we must isolate the markup a borrower is willing to pay due to its liquidity risk from the premiums demanded by lenders. We overcome these challenges by exploiting the institutional design of the euro interbank funding market, including anonymous electronic trading and central clearing.

We find that borrowers with high liquidity risk pay, on average, two basis points more for their daily funding than their low-risk peers. This markup is comparable in magnitude to the credit risk premium demanded by lenders in the unsecured interbank money market as documented by Angelini, Nobili, and Picillo (2011). In light of the large daily transaction volumes in interbank funding markets—the average bank borrows EUR 617 million per day—these results are economically meaningful. An increase of one standard deviation in liquidity risk increases the nominal costs of short-term funding by over 2.5%.

Besides relying on the market design of the euro interbank funding market to get a clean identification, we test for various alternative explanations and address omitted variable concerns. For instance, we are able to rule out that our estimates of the liquidity risk markup are contaminated by credit risk. To this end, we examine the pricing and trading behavior of banks when lending. If our results were driven by credit risk, they should become insignificant when looking at lenders because credit risk only affects borrowing rates. In line with the funding liquidity risk channel, we find that lenders with higher liquidity risk receive lower rates. We run a battery of additional robustness checks to support the validity of our measure and rule out other alternative narratives that might explain our results. Finally, we follow the methodology of Oster (2019) to bound the potential bias in our estimate of the liquidity risk markup arising from unobserved variables. We find that our quantification of the liquidity risk markup is robust to the presence of unspecified omitted variables.

Our results are important for at least three reasons. First, the funding liquidity risk channel provides a new explanation for how funding liquidity risk affects interest rates in short-term funding markets. These interest rates play a central role in financial markets, for example, as monetary policy target and benchmark for trillions of derivative contracts. Our results indicate that measuring and interpreting interest rate spreads without considering the behavior of borrowers can be misleading. Decomposing interest rates into premiums demanded by lenders and markups paid by borrowers is important to enable regulators and central banks to develop effective policies. For example, it facilitates the distinction between insolvent and illiquid banks, which require different policy responses.

Second, the funding liquidity risk channel provides an explanation for the systematic and persistent heterogeneity in funding costs. Systematic differences in short-term funding rates can undermine efficient liquidity allocation and the pass-through of monetary policy (Duffie and Krishnamurthy, 2016). Gambacorta and Shin (2018) show that higher funding costs translate into less intermediation activity, thereby weakening the transmission of monetary policy. Moreover, systematic heterogeneity can be the result of inefficiencies in the liquidity management of banks. Such inefficiencies can lead to incorrect measurements of costs, returns, and risks in numerous aspects of banks' business and trading activities, for example, through liquidity transfer pricing and funding value adjustments (BCBS, 2008). Hence, banks might pass-through the resulting differences in funding costs to their clients, thereby causing heterogeneity to spread outside the funding market.

Third, funding liquidity risk is key for financial stability. It can reinforce market illiquidity (Brunnermeier and Pedersen, 2009) and create a transmission channel between market illiquidity and credit risk (He and Xiong, 2012). These concerns become even more important in light of the transition to real-time payment systems. The need to settle payments immediately creates additional challenges for the liquidity management of banks and could potentially be a new source of financial instability. Thus, understanding the origins and dynamics of funding liquidity risk is crucial for regulators that aim to maintain financial stability and curtail the liquidity risk of banks (e.g., Basel III and the Dodd-Frank Act).

The paper proceeds as follows. In Section 2, we provide an overview of the literature and how we contribute to it. Section 3 presents the intuition behind the funding liquidity risk channel as well as a simple theoretical model. In Section 4, we provide empirical evidence for the channel. Section 5 addresses omitted variable concerns. Section 6 discusses the policy implications of our findings and Section 7 concludes.

2. Literature

This paper contributes to four strands of the literature: First, prior research on interest rate spreads in short-term debt markets suggests that interest rates deviate from the risk-free rate because lenders require a compensation for default and non-default risks (e.g., Afonso, Kovner, and Schoar, 2011; Acharya and Skeie, 2011; Filipovic and Trolle, 2013; Schwarz, 2019). The former usually refers to credit risk and the latter to market illiquidity. Imbierowicz and Rauch (2014) and Morris and Shin (2016) point out that funding liquidity risk is an important component of banks' default risk. We are the first to find that funding liquidity risk is priced within interest rates through a *borrower* markup instead of (only) through a risk premium required by lenders. We provide a new explanation, that is the funding liquidity risk channel, outlining that borrowers are willing to pay a markup due to their exposure to funding liquidity risk. To the best of our knowledge, none of the previous studies identifies and quantifies this channel.

Second, we extend the literature on short-term funding markets, which have so far mostly been studied at aggregate levels or with a focus on specific market segments in distressed periods.[3] We contribute to this literature by adopting a broader and, simultaneously, more granular perspective. Our perspective is broader because we consider crisis and non-crisis periods, which is an approach that provides valuable information regarding how funding markets function in different regimes. Simultaneously, our perspective is more granular because we analyze the behavior of individual banks instead of only market aggregates.

Other papers analyze individual banks' willingness to pay for liquidity, but at central bank auctions (e.g., Bindseil, Nyborg, and Strebulaev, 2009; Fecht, Nyborg, and Rocholl, 2011; Drehmann and Nikolaou, 2013; Cassola, Hortacsu, and Kastl, 2013). We expand on this literature in three

[3]See Bartolini, Hilton, Sundaresan, and Tonetti (2011), Gorton and Metrick (2012), Krishnamurthy, Nagel, and Orlov (2014), and Copeland, Martin, and Walker (2014) for the U.S. and Mancini, Ranaldo, and Wrampelmeyer (2016) and Boissel, Derrien, Ors, and Thesmar (2017) for Europe.

respects: (1) We identify and quantify the link between the liquidity risk of individual banks and their funding costs. By analyzing individual banks rather than the aggregate market, we reveal significant heterogeneity across funding costs of banks due to differences in exposure to liquidity shocks. (2) We provide a comprehensive analysis and consistent explanation of individual banks' borrowing *and* lending behavior across different tenors and collateral. (3) We analyze the willingness to pay on a daily basis over a much longer sample period than the existing literature, finding that banks' willingness to pay for liquidity is persistent over calm and crisis times and different monetary policy regimes.

Third, we contribute to the literature on the microstructure of short-term funding markets as our liquidity risk measure is based on the demand for immediacy of execution. There is a long history of theoretical and empirical research on trading immediacy (e.g., Demsetz, 1968; Foucault, Kadan, and Kandel, 2005; Large, 2009) and limit order book markets (e.g., Glosten, 1994; Biais, Hillion, and Spatt, 1995). Grossman and Miller (1988) present a model in which agents that are hit by liquidity shocks face a trade-off between trading with counterparties that arrive later and trading immediately with the market maker. There are very few studies on the microstructure of short-term funding markets.[4] Our study is the first to analyze the order submission of individual banks in the repo market and provides empirical evidence that liquidity risk increases the demand for immediate funding. It should be stressed that the functioning of the repo market is very different from that of equity markets studied in previous literature. As we will discuss in more detail in Section 4, rather than market making, speculation, and arbitrage, the predominant reason to trade in the GC repo market is to borrow or lend cash (and not collateral) to fulfil idiosyncratic liquidity needs. Apart from liquidity management issues, market participants are not exposed to information asymmetry and counterparty credit risk. As predicted by our simple theoretical model accommodating all these features, we provide empirical evidence that liquidity risk increases the demand for immediate funding.

Lastly, we contribute to the empirical banking literature in general by deriving and using a high-frequency measure of funding liquidity risk at the bank level. In extant literature, funding liquidity

[4] An exception for the U.S. is Furfine (1999), who examines the market microstructure of the federal funds market. Baglioni and Monticini (2008) and Abbassi, Fecht, and Tischer (2017) analyze intraday pricing patterns of European unsecured and repo rates, respectively.

risk is usually measured at the aggregate level via money market spreads such as the Libor-OIS spread. However, these measures tend to be affected by various other risk factors (e.g., Gyntelberg and Wooldridge, 2008). Similarly, the aggregate measure of Drehmann and Nikolaou (2013) based on banks' willingness to pay at central bank auctions is confounded by credit risk and strategic bidding behavior (see Cassola, Hortacsu, and Kastl, 2013). Moreover, auction-based measures are not applicable in periods when central banks supply unlimited quantities of liquidity, such as during the ECB's fixed-rate, full allotment regime since 2008. Previous bank-level studies use balance sheet information that is available only on an annual or quarterly frequency (e.g., Cornett, McNutt, Strahan, and Tehranian, 2011; Angelini, Nobili, and Picillo, 2011; Bai, Krishnamurthy, and Weymuller, 2018). In contrast, our measure is market-based and available at a daily frequency.

3. Funding liquidity risk channel

This section introduces the intuition underlying the funding liquidity risk channel. We provide a simple theoretical model to illustrate why borrowers with high liquidity risk are willing to pay a markup to lock in their funding.

3.1 Intuition and preliminary evidence

In general, funding liquidity risk emerges from a liquidity mismatch between assets and liabilities. Banks fund long-term assets with short-term liabilities. Relying more heavily on volatile sources of funding—for example, deposits from a fickle customer base or short-term interbank lending—exposes banks to regular liquidity shocks. During the day, these shocks can take various forms, such as payments to large-value payment systems, unexpected deposit withdrawals, margin calls, clients' drawing upon credit lines, or contingent payments related to a failure of a payment and settlement system (BCBS, 2013).

Funding liquidity risk is the risk of a liquidity shock leading to a binding funding constraint. In such a scenario, a bank needs to obtain funding quickly in order to balance its liquidity position before payments are settled. An urgent funding need can, for instance, arise in real-time gross settlement systems, where cash is transferred transaction-by-transaction in real time. Alternatively, margin calls can cause payment obligations on short notice. Lastly, lenders may not rollover their funding, such that banks must obtain funding until the end of the trading day to avoid having to resort to the standing facilities of the central bank.

Banks differ in their liquidity risk due to the amount of liquidity buffer they have available, their liquidity management capabilities, or the nature of their business models. Banks with a larger liquidity buffer can be more patient in obtaining funding once hit by a shock because the payment can be fulfilled using the liquidity buffer. Similarly, if banks are good at anticipating borrowing requirements, they can manage their liquidity in a manner that avoids funding constraints and the urgent need to borrow. Lastly, the business model and client base affect the size of shocks and the immediacy with which they need to be balanced in the interbank market.

Banks with high funding liquidity risk are more likely to demand immediacy of execution in the interbank market. Our model follows the literature on limit order book markets and shows that demanding immediacy increases funding cost. In a limit order book market, banks can choose between submitting market orders and limit orders. A market order guarantees the immediate execution of a trade at the best price available upon the order arrival. On the other hand, a limit order enables the trader to improve the execution price. However, the execution of a limit order is neither immediate nor certain. Consequently, banks face a trade-off between the cost of immediacy and the expected cost of delayed or no execution.[5] High funding liquidity risk implies being exposed to payment shocks that need to be urgently balanced, such that the expected cost of delayed execution is relatively high. Therefore, banks with high funding liquidity risk are likely to demand immediacy, implying that they use market orders to lock in their funding. This increases funding costs, as market orders are more costly than limit orders.

Figure 2 provides some preliminary empirical evidence for the link between funding liquidity risk, the demand for immediacy, and funding cost. It plots the average market order shares and funding costs for banks with high and low funding liquidity risk. We measure the funding liquidity risk of banks via their reliance on short-term wholesale funding. The black (grey) bars illustrate average market order shares and funding costs of bank-year observations with funding liquidity risk above (below) the median.

[5]This trade-off was first examined by Demsetz (1968) and is at the center of more recent work on limit order book markets, such as Foucault, Kadan, and Kandel (2005), Rosu (2009), and Large (2009).

[Figure 2 about here.]

In line with the funding liquidity risk channel, banks with high funding liquidity risk have a significantly higher demand for immediacy as indicated by their market order share. Simultaneously, these banks also have significantly higher funding costs. In the Internet Appendix, we run a pooled panel regression to show that the relation between funding liquidity risk and market order shares as well as funding costs is statistically and economically significant. A 10% increase in the share of short-term wholesale funding leads to a 2.1% increase in the market order share of banks and a 2.3% increase in funding costs.

It is important to note that the funding liquidity risk channel consistently applies to the lending business of banks because liquidity shocks can be either positive or negative. A positive liquidity shock leaves a bank with a funding surplus. Similar to the deficit case, such a bank must balance its books to avoid high opportunity costs. If it fails to do so until the end of the trading day, it must deposit the excess liquidity at the central bank, thereby lowering the return. Hence, banks with high liquidity risk have an incentive to demand immediacy and, thus, accept lower interest rates to avoid having to resort to the central bank. Our model, presented in the next section, provides a clear representation of how the funding liquidity risk channel works for borrowing and lending. For the sake of brevity, the empirical analysis mainly focuses on negative liquidity shocks and borrowing. We examine the lending business of banks in Section 5.1.2.

3.2 Theoretical model

3.2.1 Setup

In order to theoretically highlight the funding liquidity risk channel, we present a simple model of limit order book markets with continuous trading based on Foucault, Pagano, and Röell (2013). We focus on the interbank market, in which banks can manage their short-term funding needs during the course of the day.[6] The interbank market is structurally different from the equity market, so

[6] In Europe, the majority of short-term funding is obtained through the euro interbank repo market, which is organized as an anonymous, electronic limit order book market (e.g., Mancini, Ranaldo, and Wrampelmeyer, 2016). In the U.S., limit order books play an important role in the GCF repo market (e.g., Agueci, Alkan, Copeland, Davis, Martin, Pingitore, Prugar, and Rivas, 2014).

we cannot directly apply all concepts from the literature on equity markets. For instance, given that the asset traded is cash, there is no asymmetric information about the fundamental value of the asset. Thus, there is no natural distinction between uninformed liquidity traders and liquidity providers that are better informed. Our model fits into a wider framework of monetary policy implementation in the tradition of Poole (1968). Before entering the interbank market to manage their own liquidity deficit or surplus, banks receive liquidity from the central bank. Incoming payment shocks after the central bank's liquidity allocation create the need for interbank trading (e.g., Bech and Monnet, 2016). If banks have a liquidity surplus or deficit remaining at the end of the day, they can access the central bank's standing facilities: the deposit facility (DF) and marginal lending facility (MLF).

Banks arrive sequentially, taking into account the trade-off between immediate execution and execution price when deciding whether to post a limit or a market order. Limit orders are valid for one period. The fundamental value of cash, μ_0, is determined by the central bank and is assumed to be fixed. The central bank also determines the range of admissible interest rates $[r_{DF}, r_{MLF}]$ by demanding and supplying an infinite amount of cash at r_{DF} and r_{MLF}, respectively. When entering the market, banks either have a funding surplus or funding deficit. Banks with a funding surplus have a low private valuation for cash ($v_i = -v$) and banks with a funding deficit have a high private valuation for cash ($v_i = +v$). For simplicity, we assume that 50% of banks have a funding surplus and 50% have a deficit. Any other distribution can be easily implemented into the model.

We consider two sets of risk-neutral banks. A proportion θ of banks is exposed to shocks that must be balanced urgently (H banks), whereas $1-\theta$ of banks face shocks that are less time-sensitive (L banks). In order to distinguish between the two types, we introduce the parameter $\tau \in [0, 1]$. In particular, $1 - \tau$ is the expected probability that a funding constraint becomes binding in the subsequent period. This probability is higher for banks that are exposed to time-sensitive funding shocks. More precisely, the probability of a funding shock to become binding in the next period for a bank with type k is $\mathbb{E}^k[1 - \tau] = 1 - \tau^k$ with $k \in \{H, L\}$, where $\tau^H < \tau^L$. Consequently, τ is an inverse measure of a bank's demand for immediacy. The further τ is below 1, the higher is the demand for immediate execution. This interpretation is similar to that of Foucault, Pagano, and Röell (2013). They define $1 - \tau$ as the probability that the market closes in the next period, which makes it impossible to conduct a trade and, therefore, increases the demand for immediate execution.

3.2.2 Order choice

Bank i trades $q \in \{+1, 0, -1\}$ contracts at rate r and makes the following profit:

$$\pi_i = q(\mu_0 + v_i - r), \tag{1}$$

where $q = 1$ denotes borrowing and $q = -1$ lending. Therefore, quotes stay within the interval $[\mu_0 - v, \mu_0 + v]$, banks of type $v_i = +v$ always submit orders to borrow, and banks of type $v_i = -v$ always submit orders to lend.

Consider a borrower who submits, at time t, a limit order at rate b_t. The expected profit is

$$\mathbb{E}_t\left[\pi_t(b_t)\right] = P_t^k(b_t)\left[\mu_0 + v - b_t\right] + \Big(1 - P_t^k(b_t)\Big)\left[\mu_0 + v - r_{MLF}\right], \tag{2}$$

where $P_t^k(b_t)$ is the probability that a limit order with rate b_t is executed in time (that is, before a funding constraint becomes binding) if the bank is of type k. With probability $(1 - P_t^k(b_t))$, the order is not executed. In this case, the bank can always resort to the central bank and borrow at r_{MLF}. We define $P_t^k(b_t)$ below.

Using Equation (2), we examine the optimal rate b_t^* that the borrower must submit to the limit order book. Let $\hat{b}_{t+1}^k$ be the minimum bid rate a successor lender of type k is willing to accept using a market order. The strategy of a successor lender with high liquidity risk is to use a market order if $b_t \geq \hat{b}_{t+1}^H$. A successor lender with low liquidity risk uses a market order if $b_t \geq \hat{b}_{t+1}^L$.

Given the above strategies for the successor trader at $t+1$, Table 1 summarizes the execution probabilities of a limit order at rate b_t in t. The probability is zero if $b_t < \hat{b}_{t+1}^H$ because neither lending bank H nor L use a market order at this price. If b_t is greater or equal to $\hat{b}_{t+1}^H$ but smaller than $\hat{b}_{t+1}^L$, the limit order gets executed if the successor bank is H bank (probability $= \theta$) that wants to lend (probability $= \frac{1}{2}$), given that the funding constraint has not become binding yet (probability $= \tau^k$). If $b_t \geq \hat{b}_{t+1}^L$, both banks H and L take the order and, hence, it is sufficient if the successor is a lender and the constraint has not become binding. Consequently, the execution probability—and thereby the danger of non-execution—is driven by the probability that no matching trader arrives in the subsequent period, the proportion of H banks, and by the probability that the constraint becomes binding in the subsequent period.

[Table 1 about here.]

The optimal limit order for the borrower, b_t^*, can only be $\hat{b}_{t+1}^H$ or $\hat{b}_{t+1}^L$ because deviating from these rates leads to non-execution or no improvement in the execution probability. For any $\hat{b}_{t+1}^H$ and $\hat{b}_{t+1}^L$, the expected execution probability is smaller for H borrowers because $\tau^H < \tau^L$. The cut-off rate $\hat{a}_t^k$ that makes a borrower of type k indifferent between using a market or a limit order solves:

$$E_t\left[\pi(b_t^*)\right] = \pi(\hat{a}_t^k) \tag{3}$$

$$P_t^k(b_t^*)\left[\mu_0 + v - b_t^*\right] + \Big(1 - P_t^k(b_t^*)\Big)\left[\mu_0 + v - r_{MLF}\right] = \mu_0 + v - \hat{a}_t^k, \tag{4}$$

where the left-hand side is the expected profit from posting a limit order at b_t^*. The right-hand side is the profit from using a market order that is executed immediately at $\hat{a}_t^k$. Solving for the cut-off borrowing rate $\hat{a}_t^k$ yields

$$\hat{a}_t^k = P_t^k(b_t^*)\left[b_t^*\right] + \Big(1 - P_t^k(b^*)\Big)\left[r_{MLF}\right]. \tag{5}$$

Hence, the cut-off borrowing rate is a weighted average of the limit order rate and the outside cost. The weights are determined by the execution probability $P_t^H < P_t^L$. The argument for the lender is analogous. The cut-off rate that makes the lender indifferent between using a market or limit order is

$$\hat{b}_t^k = P_t^k(a_t^*)\left[a_t^*\right] + \Big(1 - P_t^k(a_t^*)\Big)\left[r_{DF}\right]. \tag{6}$$

Based on the cut-off rates, Proposition 1 shows that banks with high liquidity risk use more market orders than banks with low liquidity risk.

Proposition 1 (Order submission).

(i) Borrowers with high liquidity risk have a higher cut-off rate at which they are willing to use a market order than borrowers with low liquidity risk.

$$\hat{a}_t^H \geq \hat{a}_t^L.$$

(ii) Lenders with high liquidity risk have a lower cut-off rate at which they are willing to use a market order than lenders with low liquidity risk.

$$\hat{b}_t^H \leq \hat{b}_t^L.$$

Proof. The results of Proposition 1 follow directly from Equations (5) and (6) and the fact that $P_t^H < P_t^L$. □

3.2.3 Funding cost

Next, we derive the equilibrium interest rates to analyze banks' funding cost. The parameters (τ, μ_0, v) are time-invariant and hence banks' strategies do not depend on time because they face the same decision problem in each period. Therefore, we can focus on steady-state equilibria, which implies that

$$\hat{b}_t = \hat{b} \text{ and } \hat{a}_t = \hat{a} \ \forall t. \tag{7}$$

Using Equations (5) to (7), we compute banks' equilibrium bids, offers, and cut-off rates:[7]

$$\hat{a}^H = \frac{2}{2+\tau^H\theta} r_{MLF} + \frac{\tau^H\theta}{2+\tau^H\theta} r_{DF} \tag{8}$$

$$\hat{b}^H = \frac{\tau^H\theta}{2+\tau^H\theta} r_{MLF} + \frac{2}{2+\tau^H\theta} r_{DF} \tag{9}$$

$$\hat{a}^L = \frac{2}{2+\tau^L} r_{MLF} + \frac{\tau^L}{2+\tau^L} r_{DF} \tag{10}$$

$$\hat{b}^L = \frac{\tau^L}{2+\tau^L} r_{MLF} + \frac{2}{2+\tau^L} r_{DF}. \tag{11}$$

Table 2 summarizes the order submission strategies of high- and low-liquidity-risk banks for all

[7] Derivations can be found in the Appendix.

relevant scenarios. The first two columns present the type of bank that is arriving to the market and the state of the order book at the time of arrival. Column three highlights the preferred order type and column four depicts the rates between which the bank is indifferent. For example, borrower H—who arrives in the market when there is an ask quote at $\hat{a}^H$—is indifferent between a market order at $\hat{a}^H$ or posting a limit order at $\hat{b}^H$ or $\hat{b}^L$.

[Table 2 about here.]

Comparing the preferred order types for banks H and L, Table 2 indicates that banks with high liquidity risk use more market orders than their low-risk peers. For all four states of the order book, the interest rates paid (received) by high-liquidity-risk borrowers (lenders) are larger (smaller) or equal to the interest rates paid (received) by low liquidity risk borrowers (lenders). We summarize this finding in Proposition 2.

Proposition 2 (Funding cost).
In equilibrium, banks with high liquidity risk

(i) pay higher interest rates when borrowing and

(ii) receive lower interest rates when lending

than banks with low liquidity risk.

Proof. The results of Proposition 2 follow directly from Equations (8) to (11) and Table 2. □

The difference in interest rates paid/received by high- and low-liquidity-risk banks depends on the expected bid/ask spread. From Equations (8) to (11), we obtain three possible bid/ask spreads, depending on the sequence with which banks arrive in the market:

$$\hat{a}^H - \hat{b}^H = \frac{4 - \tau^L \tau^H \theta + 2(\tau^L - \tau^H \theta)}{(2+\tau^L)(2+\tau^H\theta)}(r_{MLF} - r_{DF}) \text{ with probability } \theta^2 \tag{12}$$

$$\hat{a}^H - \hat{b}^L = \frac{4 - \tau^L \tau^H \theta}{(2+\tau^L)(2+\tau^H\theta)}(r_{MLF} - r_{DF}) = \hat{a}^L - \hat{b}^H \text{ with probability } 2(\theta - \theta^2) \tag{13}$$

$$\hat{a}^L - \hat{b}^L = \frac{4 - \tau^L \tau^H \theta - 2(\tau^L - \tau^H \theta)}{(2+\tau^L)(2+\tau^H\theta)}(r_{MLF} - r_{DF}) \text{ with probability } (1-\theta)^2. \tag{14}$$

The higher the proportion of high-liquidity-risk banks, θ, the greater the expected bid/ask spread and, hence, the greater the heterogeneity in funding costs.

4. Empirical analysis

The goal of our empirical analysis is to provide evidence for the funding liquidity risk channel and to quantify the markup that borrowers are willing to pay due to their funding liquidity risk. We face three main identification challenges: First, we must isolate funding transactions from transactions with other intentions, such as market making, speculation, arbitrage, or sourcing a specific security. Second, we must construct a proxy for the idiosyncratic funding liquidity risk of borrowers because it is not directly observable. Finally, we must isolate the markup a borrower is willing to pay due to its liquidity risk from the premiums required by lenders. We overcome these challenges by exploiting the institutional design of an important segment of the European short-term funding market: the General Collateral (GC) repo market.[8]

4.1 Data and the repo market

We use data from Eurex Repo AG, a major trading platform in the euro interbank repo market. In this market, a CCP is at the center of each transaction, functioning as a borrower to every lender and a lender to every borrower. The CCP is responsible for risk management and determines haircuts centrally for all market participants. Repos are traded anonymously via a transparent electronic order book.

We focus on overnight (ON) repos with collateral from the GC Pooling ECB basket to ensure that neither differences in term nor collateral risk can impact our results.[9] In a GC repo, borrowers are free to supply any security included in a predefined basket as collateral. The GC Pooling ECB basket, is one of the major GC baskets in Europe. It includes approximately 3,000 securities that are eligible for open market operations at the ECB and have been rated at least A/A3. The addendum “Pooling” reflects the internationality of the basket. Compared to common GC baskets, which normally cover only one country, the GC Pooling ECB basket includes bonds from Austria, Belgium, France, Germany, Slovenia, the Netherlands, and international Eurobonds (XS ISINs).

[8] See Mancini, Ranaldo, and Wrampelmeyer (2016) and Nyborg (2016) for a detailed discussion on the market structure of the euro interbank repo market.

[9] For instance, Bartolini, Hilton, Sundaresan, and Tonetti (2011) show that repo rates secured by Treasury securities trade $6 - 7$ basis points lower than those secured by agency securities or MBS.

The bond issuer must be established in the European Economic Area (EEA) or in one of the non-EEA G10 countries (that is, the U.S., Canada, Japan, or Switzerland).

Our data set includes transactions from January 2006 to December 2016, covering 2,807 trading days. It covers 95 banks from over 10 countries that conduct 95,462 trades, amounting to a total volume of EUR 23 trillion. For each trade, the following information is available: time of the trade, collateral basket, trade volume, repo rate, and an anonymous bank ID of the borrower and lender. We match the repo data with annual bank balance sheet information from SNL Financial using the matching from di Filippo, Ranaldo, and Wrampelmeyer (2017).

The daily repo trading volume averages approximately EUR 27 billion without double counting of lending and borrowing. GC Pooling repos account for 44% of the CCP GC repo market, 29% of the total GC market, and 88% of the total unsecured interbank market.[10] ON repos account for more than 42% of the total turnover at Eurex between 2006 and 2016.[11] The volume of overnight repos follows the same trend as the overall volume. Figure 3 shows aggregate market developments in repo rates and volumes during our sample period.

[Figure 3 about here.]

Panel (a) of Table 3 presents summary statistics for the repo market activity of individual banks. We measure the relative funding costs of banks through their excess rates, which we compute as the volume-weighted average repo rate paid by bank i on day t, $r_{i,t}$, minus the daily volume-weighted average of all overnight transactions from the GC Pooling ECB basket, $\bar{r}_t$:

$$r^e_{i,t} = r_{i,t} - \bar{r}_t. \tag{15}$$

[10]The quarterly cumulative turnover of the secured (repo) and unsecured money market in 2015 is approximately EUR 28 trillion and EUR 2.8 trillion, respectively. The share of GC repos is approximately 30%, of which 66% are centrally cleared through a CCP, 26% are bilateral, and 8% are tri-party repos (European Central Bank, 2015; European Money Market Institute, 2017).

[11]We also analyze repos with tomorrow-next (TN) and spot-next (SN) tenors as a robustness check in Section 4.4.3. Together with ON repos, these products account for more than 86% of the overall trading volume. ON, TN, and SN are all one-day repos that differ in terms of their purchase and repurchase dates. An ON repo runs from today (t) to tomorrow ($t+1$), TN from $t+1$ to $t+2$, and SN from $t+2$ to $t+3$.

On average, banks borrow EUR 617 million per day, split into 2.56 trades. We define a bank's experience as the cumulative number of trading days, that is, when a bank trades for the first time, this variable takes the value 1; on the second trading day, it takes the value 2, and so on. Panel (b) of Table 3 indicates that our sample covers banks ranging from a balance sheet size of EUR 1 billion to EUR 3,544 billion, with different levels of profitability, leverage, balance sheet structures, and credit risk.

Banks with high funding costs have lower trading volumes and are less experienced than their peers. Interestingly, they are also smaller in terms of their total assets. Banks with high funding costs have higher CDS spreads indicating that funding liquidity risk and credit risk are correlated and, hence, controlling for credit risk in our regression analysis is important.

[Table 3 about here.]

The GC Pooling repo market has unique characteristics that help us address our identification challenges. The CCP-based structure with anonymous trading via an electronic trading platform rules out various potential drivers of interest rates. For instance, asymmetric information, trading relationships, and search costs have been shown to be important drivers of interest rates in unsecured and non-anonymous fixed-income markets (e.g., Ashcraft and Duffie, 2007; Temizsoy, Iori, and Montes-Rojas, 2015; Craig, Fecht, and Tümer-Alkan, 2015), but cannot impact interest rates in the CCP-based euro repo market. Due to the fact that haircuts are determined by the CCP and are the same across all market participants, repo rates are not blurred by heterogeneity in haircuts and, thus, they fully capture differences in banks' (repo) funding costs. In the following three subsection, we discuss in more detail how we utilize the market structure to overcome our three identification challenges.

4.2 Funding-driven market

In order to address our first identification challenge—that is, isolating funding transactions—we utilize the fact that the GC repo market is a funding market. In a repo based on the GC Pooling ECB basket, borrowers are free to supply any of the 3,000 securities as collateral. Ex ante, lenders do not have knowledge of the exact security they will receive and, hence, they cannot use this market to source a specific asset. Therefore, the GC repo market is widely recognized as funding market that is driven by the demand and supply of cash.[12] Consequently, restricting our analysis to repos from the GC Pooling ECB basket ensures that we exclusively consider funding trades.

Figure 4 presents additional evidence that GC Pooling repo trading is driven by the need for funding. It plots the distribution of banks' daily net-to-gross ratios, defined as net borrowing over total borrowing and lending. A ratio of 1 indicates that a bank only borrows on a given day. Correspondingly, a ratio of -1 indicates pure lending. Banks are (almost) exclusively on one side of the market on a given day, meaning they either only borrow or only lend. This confirms that the GC Pooling repo market is a funding market, where banks balance their in- and outflows of liquidity. Alternative trading strategies, such as market making, speculation, or (cross-basket) arbitrage, would require banks to be equally active on both sides of the market (e.g., Agueci, Alkan, Copeland, Davis, Martin, Pingitore, Prugar, and Rivas, 2014). Additionally, we find that those banks which are on both sides of the market on a given day on average do not make a profit from their trading.

[Figure 4 about here.]

4.3 Measuring idiosyncratic funding liquidity risk

In order to address the second identification challenge—that is, how to measure liquidity risk—we utilize the limit order book structure of the GC repo market. As motivated in Section 3, banks' demand for immediate execution in the interbank market is a function of their liquidity risk. In limit order books, the demand for immediate execution is observable, meaning that we can measure banks' demand for immediate funding via their order choice. More precisely, banks with high liquidity risk demand immediacy and thus prefer market orders to lock in their funding. Against this background, we derive our proxy for idiosyncratic liquidity risk from banks' volume-weighted shares of market orders. We can do this because the particular market design of the euro repo market rules out various other reasons why banks might want to use market orders. For instance, as shown in the previous section, market making does not play a role. The repo market is

[12] There is also a special collateral repo market. In this market, the borrower and lender agree to use a specific asset as collateral. Therefore, special collateral repos are security-driven and rates are determined by the demand and supply of securities instead of cash.

a funding market, such that a segmentation of participants into noise traders and informed traders known from equity markets does not apply. We control for the few remaining determinants of order choice that may play a role in the euro GC repo market when constructing the measure below.

4.3.1 Constructing the measure

In Section 3, we provide some preliminary empirical evidence for the link between funding liquidity risk and demand for immediacy, using banks' share of short-term wholesale funding as a proxy for funding liquidity risk. The disadvantage of this proxy is that it is not very accurate and only available at a yearly frequency and for a subset of our banks. In order to get daily variation in funding liquidity risk at the individual bank level, we exploit variation in the daily volume-weighted market order share of banks. To make our measure more precise, we only use the variation in the market order share that is orthogonal to other potential determinants of banks' order choice. More precisely, we use the residuals from the following regression model as our proxy for idiosyncratic funding liquidity risk:

$$MOS_{i,t} = \alpha + X_{i,t}\gamma + \varepsilon_{i,t}, \tag{16}$$

where $MOS_{i,t}$ is the volume-weighted market order share of bank i on day t and $\varepsilon_{i,t}$ is the error term. $X_{i,t}$ is a matrix of potential determinants of banks' order choice that are unrelated to funding liquidity risk.[13] The matrix includes both trade-level determinants as well as common bank-level controls: banks' logged repo volume in EUR million ($Volume$), trade time ($TradeTime$), logged cumulative number of trading days ($Experience$), logged size of total assets in EUR billion ($TotalAssets$), return on average assets ($ROAA$), debt-to-equity ratio ($Leverage$), and logged CDS spreads (CDS).[14]

We include CDS spreads to avoid that our liquidity risk measure is confounded by credit risk.

[13] Note that $TradeTime$ might also eliminate some of the variation in liquidity risk to the extent that it captures the time of arrival of banks in the market. The later a bank arrives, the more time-sensitive a funding shock could be, as markets tend to be closing soon. However, $TradeTime$ only measures the execution time of a trade. In particular in the case of limit orders, the execution time of a trade can be far away from the market arrival of a bank. In the Internet Appendix, we run one specification without $TradeTime$. The results remain almost unchanged.

[14] For more information on these variables, see Table A.1 in the Appendix.

As discussed in Section 4.1, the CCP-based anonymous market design controls for any direct impact of credit risk. However, there might be an indirect channel that links credit risk to banks' order choice in the repo market. Banks with high credit risk might have more difficulties to get funding outside the repo market (e.g., in the unsecured market) and hence they are forced to act more aggressively in the repo market to lock in their funding. Against this background, we decided to include CDS spreads in our baseline specification. Balance sheet data and CDS spreads are not available for all banks, thereby reducing the number of observations. In the Internet Appendix, we discuss this in more detail and show that our results are robust to changing the composition of control variables, such as leaving out CDS spreads or adding bank and time fixed effects.[15]

Panel (a) of Table 4 presents summary statistics for our measure, which we call *LiquidityRisk*. Being a residual, it is centered around zero by design. The second and third rows present the summary statistics of *LiquidityRisk* for banks with high and low funding costs, respectively. In line with the funding liquidity risk channel, banks with higher funding costs also have higher funding liquidity risk. Before testing this relationship more thoroughly, we provide additional evidence for the validity of our measure.

[Table 4 around here.]

4.3.2 Testing the validity of the liquidity risk measure

To support the validity of our proxy, we examine its relationship to alternative measures of funding liquidity risk. We begin by examining conventional measures that are derived from balance sheet data, such as the share of short-term wholesale funding of banks, which we have already used as a proxy for funding liquidity risk in Figure 2 in Section 3.1. Additionally, we compute the fraction of demand deposits—which are redeemable without prior notice—over total deposits. Panel (b) of Table 4 presents the summary statistics of *LiquidityRisk* for banks with high and low funding liquidity risk as indicated by these balance sheet measures. As expected, *LiquidityRisk* is higher for banks that rely heavily on short-term wholesale or deposit funding.

In our second validity test, we examine if *LiquidityRisk* captures increased liquidity risk that

[15]In Section 5, we provide additional evidence that our measure is not confounded by credit risk or other omitted variables.

originates from liquidity shocks. This is a direct test of the funding liquidity risk channel, which posits that liquidity risk originates from the exposure to liquidity shocks. We identify liquidity shocks as a change in the direction of trading from lending to borrowing. In the previous section, we have shown that banks enter the GC Pooling market first and foremost to manage their funding. Therefore, they are usually only on one side of the market, implying that they either only borrow or only lend on a given day. When a bank enters the market as a lender and subsequently during the day switches to borrowing, this is most likely caused by a negative liquidity shock that forces the bank to correct its funding position.

Table 5 presents the results of a logistic regression evaluating if our measure for liquidity risk captures the risk originating from liquidity shocks. The dependent variable is a binary variable that becomes 1 if *LiquidityRisk* is positive. The independent variable, *Switch*, is also a binary variable. It takes the value 1 on days when a bank enters the market as lender and later switches to borrowing. Hence, *Switch* indicates if banks are exposed to a liquidity shock on a given day. The odds of having a positive liquidity risk more than double in the presence of a liquidity shock.[16] Note that according to the funding liquidity risk channel, a liquidity shock should only lead to high funding pressure if it is time-sensitive, that is, if the bank needs the liquidity immediately. In contrast to our measure of funding liquidity risk, *Switch* does not capture the time-sensitivity of liquidity shocks. Therefore, in our third validity test, we exploit a setting where the time-sensitivity of shocks is observable.

[Table 5 around here.]

The third validity test examines banks' *LiquidityRisk* at the end of the ECB's maintenance periods. In order to fulfill the ECB's reserve requirements, banks need to hold a certain average amount of liquidity over the reserve maintenance period. If banks have not yet fulfilled these requirement toward the end of the period, they are obliged to acquire the missing reserves to avoid fines.[17] Consequently, liquidity shocks at the end of the maintenance period are more likely to be

[16]In the Internet Appendix, we present a contingency matrix showing the joint frequency distribution of *LiquidityRisk* and *Switch*.

[17]In contrast to the Federal Reserve, the ECB does not allow banks to carry over any reserve deficits/surpluses into the following reserve maintenance period.

time-sensitive and, hence, we expect our measure for liquidity risk to be higher for those days.

In Table 6, we focus on the last three days of the maintenance period t, $t-1$, and $t-2$. After being hit by a liquidity shock on these days, banks have three possibilities of obtaining funding to fulfill the reserve requirement: (1) They can conduct an ON repo at t, (2) a TN repo at $t-1$, (3) or a SN repo at $t-2$. All three strategies guarantee funding on the last day of the maintenance period.[18] Table 6 presents the *LiquidityRisk* in excess of the maintenance period average for banks trading ON, TN, and SN repos. The columns depict the last three days of the maintenance period. The numbers in bold identify the repo contracts that provide funding on the last day of the maintenance period. For instance, one day before the end of the maintenance period ($t-1$), conducting a TN repo enables banks to lock in funding on the last day of the period. In line with our expectations, *LiquidityRisk* is significantly greater for those contracts that lock in liquidity on the last day of the maintenance period.

[Table 6 around here.]

4.4 Quantifying the funding liquidity risk markup

In this section, we quantify the effect of funding liquidity risk on funding costs, that is, we quantify the markup that borrowers are willing to pay to lock in their funding following a liquidity shock. The market structure of the euro GC repo market also allows us to tackle the third identification challenge, which requires us to decompose repo rates into the markup that borrowers are willing to pay due to their funding liquidity risk and the premium required by lenders as compensation for credit and (market) liquidity risk. Because trading in the market is anonymous and conducted via a CCP, there is no direct exposure between borrowers and lenders and counterparty identities are not revealed. Hence, lenders cannot demand risk premiums that are specific to individual borrowers. Therefore, we can be sure that repo rates in the CCP-based GC repo market do not carry any lender premiums specific to individual borrowers.

[18] Recall, that ON repos run from today (t) to tomorrow ($t+1$), TN from $t+1$ to $t+2$, and SN from $t+2$ to $t+3$.

4.4.1 Baseline analysis

Due to the favorable market design of the CCP-based GC repo market, we can run the following regression in order to quantify the borrower markup, which will be measured by the coefficient β:

$$r_{i,t}^{e} = \beta \ LiquidityRisk_{i,t} + X_{i,t} \ \theta + \eta_i + \lambda_t + \varepsilon_{i,t}, \tag{17}$$

where $r_{i,t}^{e}$ is the excess repo rate of bank i on day t, $LiquidityRisk_{i,t}$ is our proxy for banks' idiosyncratic funding liquidity risk, $X_{i,t}$ is a matrix of control variables, η_i is a fixed effect for bank i, λ_t is a fixed effect for day t, and $\varepsilon_{i,t}$ is the error term. The matrix of controls is identical to the first stage in Equation (16). It includes banks' logged daily repo volume in EUR million ($Volume$), average trade time ($TradeTime$), logged cumulative number of trading days ($Experience$), logged size of total assets in EUR billion ($TotalAssets$), return on average assets ($ROAA$), debt-to-equity ratio ($Leverage$), and logged CDS spreads (CDS).

Columns (1) to (3) of Table 7 present the regression results of our first and second stage baseline specification. All models are estimated using OLS and robust standard errors that are clustered at the bank-day level. In the first stage (Column (1)), all regressors except for $Volume$ are insignificant. In particular, the coefficient of CDS spreads is insignificant. This is in line with the fact that the market design controls for any direct impact of credit risk. It also suggests that credit risk does not have any indirect impact on funding costs.

In the two specifications of the second stage regression in Columns (2) and (3), the coefficient of $LiquidityRisk$ is positive and statistically significant, ranging between 1.6 and 2.0. Consequently, borrowers with high liquidity risk pay up to 2 basis points more on a given day than their low-risk peers. In light of the large daily transaction volumes in interbank funding markets—on average, banks borrow EUR 617 million per day—these results are not only statistically significant but also economically meaningful. A one standard deviation increase in liquidity risk increases the nominal costs of short-term funding by over 2.5%. Funding liquidity risk has a similar magnitude as the impact of credit risk in unsecured markets, as documented by Angelini, Nobili, and Picillo (2011). In their paper, a downgrade in a bank's Fitch individual rating from A (best) to C (middle of the range) corresponds to an increase in rates spreads of 0 to 5 basis points depending on the sample and econometric specification. In addition, it stands to reason that we only measure the lower bound of the effect because the CCP-based GC repo market is one of the most liquid and sophisticated segments of the euro funding market. Moreover, the maximum effect is capped by the bid-ask spread. Even if a bank is willing to pay higher rates, it can always accept the best existing limit order from the order book. This creates a cap for its maximum cost and biases our results downward. Hence, in markets without a limit order book, it seems likely that the effect has an even larger magnitude.

[Table 7 around here.]

$TradeTime$ is the only control variable that has a statistically and economically significant effect on funding costs. Trades that are executed later in the day decrease funding costs by approximately 0.3 basis points per hour. This effect is known as intraday interest rate and has been analyzed by, among others, Furfine (2001), Baglioni and Monticini (2008), and Abbassi, Fecht, and Tischer (2017), who find a similar magnitude for the intraday rate. It is important to note that decreasing repo rates during the day are not in opposition to the funding liquidity risk channel. The channel does not make predictions regarding the level of interest rates. Instead, it provides an explanation for the cross-sectional distribution around the average market rate.

4.4.2 Funding liquidity risk markup in different subperiods

In this section, we investigate how the relationship between liquidity risk and funding costs changes across two major subsamples of the data: the financial crisis and the floor system. The former is defined as the time between July 2007 and July 2009 and is characterized by high levels of volatility, uncertainty, and illiquidity in financial markets. The floor system refers to the time after the allotment of the two major long-term refinancing operations (LTROs) of the ECB around the beginning of 2012. It also includes European quantitative easing (QE), which began in March 2015. Both policies produced high levels of excess reserves, driving money market rates to the lower bound of the ECB's interest rate corridor.

Columns (4) and (5) of Table 7 present the regression results. High funding liquidity risk is more costly during crises and less costly in a floor system. The coefficient of $LiquidityRisk$ is close to three times larger in the crisis period. This result is intuitive as it implies that high liquidity risk is more costly when liquidity is scarce. It is also in line with our theory, which shows that a higher proportion of banks with high liquidity risk increases the funding cost differential between high- and low-liquidity risk banks.

Our findings across subperiods highlight a link between funding liquidity risk and market liquidity in funding markets. Banks with high funding liquidity risk have a higher demand for immediacy and are, therefore, willing to pay the bid/ask spread in the funding market. During crises, market liquidity in the funding market is low and hence bid/ask spreads are high. In a floor system, funding markets are liquid due to the excess liquidity and, hence, bid/ask spreads are low. Consequently, having high idiosyncratic funding liquidity risk is particularly costly when market liquidity in funding markets is low. This finding complements the extant literature that links asset market liquidity and funding illiquidity (e.g., Brunnermeier and Pedersen, 2009).

4.4.3 Robustness checks

In this section, we provide additional analyses to support the robustness of our empirical findings. We show that the size of the funding liquidity risk markup is robust to different econometric specifications, that it is not driven by extreme observations, and that it is similar across different tenors and collateral baskets.

Dynamic panel model. In light of the persistence in funding costs, we extend our main regression model to allow for autocorrelation of the dependent variable by adding its first lag to the model:

$$r^e_{i,t} = \rho \; r^e_{i,t-1} + \beta \; LiquidityRisk_{i,t} + X_{i,t} \; \theta + \eta_i + \varepsilon_{i,t}. \tag{18}$$

We estimate this model using the two-step Arellano and Bond (1991) dynamic panel estimator. Panel estimators usually control for unobserved heterogeneity by first-differencing. Since our data is unbalanced, we instead apply forward orthogonal deviations as in Arellano and Bover (1995). In order to keep the number of instruments small and avoid instrument proliferation, we exclude the time fixed effects and restrict lags for the GMM moment conditions to five.[19]

[19]Control variables enter with their first lag and beyond, which is equivalent to treating them as predetermined. The results remain numerically similar and qualitatively equivalent when all variables are entered beginning with their second lag and, hence, treating everything as endogenous.

Column (1) of Table 8 present the results. Similar to our main results, the coefficient of *LiquidityRisk* is positive and significant. The tests for first- and second-order autocorrelation indicate that our model is well specified using the first lag of the dependent variable.

[Table 8 around here.]

Relative frequencies. To eliminate the possibility that our results are driven by outliers in the excess rate, $r^e_{i,t}$, we employ the relative frequency of having a positive excess rate, $RF_{i,t}$, as an alternative measure for banks' funding costs:

$$RF_{i,t} = \frac{\sum_{q=1}^{Q_{i,t}} \mathbb{1}(r^e_{i,t,q} > 0)}{Q_{i,t}}, \tag{19}$$

where $\mathbb{1}$ is the indicator function, $r^e_{i,t,q}$ is bank i's excess rate from its q-th trade on day t, and $Q_{i,t}$ denotes the total number of trades for each bank and day. A relative frequency of 0.5 implies that bank i pays more than the daily volume-weighted average repo rate in 50% of its trades. While $r^e_{i,t}$ is the more direct measure, $RF_{i,t}$ is robust to outliers because it is between 0 and 1 by construction.

Figure 5 replicates Panel (a) of Figure 1 using relative frequencies instead of excess rates. The borrower located at the extreme left has the lowest RF of below 0.3, implying that this bank pays more than the daily average in less than 30% of its trades. The borrower on the right end of the distribution pays more than the daily average in approximately 90% of its trades.

[Figure 5 around here]

Column (2) of Table 8 presents the regression results of the main regression model using $RF_{i,t}$ instead of $r^e_{i,t}$ as the dependent variable. The results are similar; in particular, *LiquidityRisk* is positive and significant in all specifications. The likelihood of paying more than average increases by approximately 38% for banks with high liquidity risk.

Different tenors and collateral baskets. As a final robustness check, we repeat our regression analysis using repos with alternative tenors and collateral baskets to support the external validity of our results. We estimate our main regression model (Equation (17)) using TN and

SN repos as well as repos with collateral from the riskier GC Pooling ECB EXTended basket.[20] Columns (3) and (4) of Table 8 present the results. The positive relationship between liquidity risk and funding costs is evident in both specifications. For the ECB EXTended basket, the coefficient of *LiquidityRisk* has a similar magnitude as in our baseline specification. For TN and SN repos, the magnitude is slightly smaller, which makes sense because time sensitivity should generally be lower for these tenors because a bank can always fall back on an ON repo if it is unable to execute a TN or SN repo. In other words, instead of conducting a TN (SN) repo today, a bank can do an ON repo tomorrow (the day after tomorrow).

5. Omitted variables concerns

The market design of the GC Pooling repo market rules out the most obvious and important confounding variables. However, there might still be concerns about potential omitted variables that bias our results. In this section, we provide further analyses to show that credit risk, preferred habitat, and collateral holdings do not affect our measure and our estimates for the size of the funding liquidity risk markup. Moreover, we implement a one-step estimation approach and apply the methodology of Oster (2019) to bound the effect of potential omitted variables more generally.

5.1 Credit risk

A potential concern about the validity of our measure is that it picks up forms of credit risk that are not captured by a bank's 5-year CDS spread which we include as control variable in our regression analysis. We address this concern in multiple ways. First, rather than controlling for the level of CDS spreads, we include changes in CDS spreads to better capture innovations in credit risk. Second, we repeat our analysis focusing on periods in which credit risk plays a minor role and examine if our results hold. Finally, we exploit the richness of our data set and redo the analysis with lender data as the trading activity of lenders should be unaffected by credit risk.

[20] The ECB EXTended basket includes around 14,000 ECB eligible securities with the minimum rating requirement being equal to the one applied by the ECB. Compared with the GC Pooling ECB basket, the list of eligible securities includes riskier securities. More precisely, the location of issuance is extended to Finland, Ireland, Italy, Luxembourg, Malta, and Spain.

5.1.1 Innovations in credit risk and subsample analysis

In the first stage of our baseline regression model, we include CDS spreads to make sure that the residual, which ultimately serves as our measure, is free of credit risk. The first stage regression results of our baseline specification can be found in Column (1) of Table 7. The coefficient for the CDS spreads is insignificant, indicating that credit risk does not impact the order choice of banks in the anonymous CCP-based repo market. Hence, already starting point for constructing our liquidity measure, the market order share, seems to be unrelated to credit risk. Consequently, the measure itself will also be unrelated to credit risk.

Table 9 presents two alternative ways of controlling for credit risk. In order to better capture innovations in credit risk, we include CDS spreads in first-differences. If credit risk impacts our measure, it would be particularly strong when there is a shock to banks' credit risk, that is, when CDS rates move strongly. Column (1) of Table 9 shows the first-stage results. The coefficient of ΔCDS is insignificant. This is in line with our baseline results and the fact that credit risk plays no role for the order choice of banks and thus for our measure. Additionally, as shown in Column (2), our coefficient of interest ($LiquidityRisk$) hardly changes compared to the baseline specification. It remains at about 2 basis points.

Ratings are an alternative way of capturing the credit risk of banks. Credit risk should play a dominant role particularly for the behavior of banks around rating changes. To ensure that our measure for liquidity risk is not driven by these rating shocks, we conduct a subsample analysis, dropping all observations two weeks around changes in Standard & Poor's credit ratings of banks. Results presented in Column (2) and (3) of Table 9 are consistent with our baseline results. In particular, the coefficient of interest ($LiquidityRisk$) hardly changes when dropping observations around rating changes.

[Table 9 around here.]

5.1.2 Lender analysis

In this subsection, we provide additional evidence that our results are not driven by credit risk. To this end, we examine the trading and pricing behavior of banks when lending. The idea behind this test is that the borrowing and lending behavior of banks differs depending on whether it is driven by funding liquidity risk or credit risk. The funding liquidity risk channel predicts that banks with high liquidity risk have a high demand for immediacy (and hence a high market order share) irrespective of whether they borrow or lend. Negative shocks lead to demand for borrowing immediacy and positive shocks lead to demand for lending immediacy. According to the indirect credit risk channel, on the other hand, a high demand for immediacy should only exist for borrowers.[21] A bank with high credit risk might have a high demand for borrowing immediacy because credit risk impedes the acquisition of liquidity from alternative sources, such as the unsecured funding market. However, there is no reason why banks with high credit risk should have a systematically high demand for lending immediacy. Against this background, we are able to construct a simple test for the presence of the indirect credit risk channel: If credit risk drives our results, we should find significant results only for borrowers. Finding significant results for borrowers *and* lenders would strongly support the funding liquidity risk channel.

Examining the repo market from the perspective of lenders brings about two changes. First, the repo rate is not a cost anymore but a revenue. Second, demand for immediacy is the urgent need to lend instead of the need to borrow. As motivated in Section 3, the funding liquidity risk channel posits that lenders face the same pressure to efficiently manage their liquidity as borrowers. Lenders with a funding surplus can use the repo market to safely invest their excess liquidity. If they fail to do so until the end of the trading day, they must resort to the deposit facility at the ECB.[22] The latter normally pays less and, hence, represents an opportunity cost for repo lenders, just as the marginal lending facility does for borrowers.

Repeating our analysis for lenders reveals that funding liquidity risk is also a major driver of heterogeneity in interest rates when lending. The heterogeneity of interest rates is presented in Figure 6. Columns (5) and (6) of Table 9 show the first- and second stage regression results for

[21]Recall, that we control for any direct effects of credit risk via the market design. However, there might be an indirect channel: Borrowers with high credit risk might have more difficulties to get funding outside the repo market (e.g., in the unsecured market) and hence they are forced to act more aggressively in the repo market to lock in their funding.

[22]The unsecured money market would be another alternative. However, unlike unsecured borrowing, unsecured lending is conceptually rather different from lending via repos, (credit) risk management considerations come into play. On the other hand, lending to the central bank is similar to using CCP repos because it is secured and without credit risk.

lenders.[23] The lender perspective is completely consistent with what we find for borrowers in the sense that revenues are heterogeneous and driven by liquidity risk. This allows us to reject the alternative hypothesis that differences in funding costs arise due to credit risk.

[Figure 6 around here.]

5.2 Preferred habitat and collateral holdings

Banks might have a preferred habitat for holding cash, specific money market instruments (e.g., Ogden, 1987), certain (HQLA) assets due to regulatory requirements, or they are specialized in particular segments of the repo market. If a bank has a preferred habitat or is specialized in a specific segment of the repo market, we would expect this bank to behave differently in this segment than in others. Similarly, if a bank holds assets that are tailored to a certain collateral basket, it might have a higher willingness to pay in this basket, but not in others. Additionally, while specific collateral holdings might incentivize a bank to borrow in a certain basket, they also disincentivise the bank to lend in this basket. In a nutshell, preferred habitat, specialization, and heterogeneous collateral holdings lead to differing behavior of banks across different segments of the repo market.

According to the funding liquidity risk channel, on the other hand, the behavior of banks should not differ across different segments of the repo market. It only depends on their exposure to idiosyncratic liquidity shocks, which is independent of the market segment and independent of whether a bank borrows or lends. The funding liquidity risk channel predicts that the same banks that are willing to pay higher rates when borrowing also accept lower rates when lending, independently of the collateral or the tenor of a repo.

Panel (a) of Figure 7 presents the performance of our banks as measured by their relative frequency of having a positive excess rate, RF, when borrowing or lending. It suggests that banks that perform well (pay less) as borrowers also tend to perform well (receive more) as lenders. In other words, banks with low funding costs when borrowing tend to make high revenues when lending and vice versa. Panel (b) presents the performance of banks when borrowing in the ECB

[23] We also test the validity of our proxy for the liquidity risk of lenders. In other words, we examine whether the proxy is able to capture increased risk from liquidity shocks to lenders. The results are presented in the Internet Appendix and are similar to the case of borrowers. Hence, our proxy also captures the increase in liquidity risk from liquidity shocks for lenders.

or the riskier ECB EXTended basket. Banks that pay a markup in the ECB basket also tend to pay a markup in the ECB EXTended basket. The figure for the performance of banks across different tenors looks similar and can be found in the Internet Appendix. Overall, these findings are consistent with the funding liquidity risk channel: Some banks are systematically more exposed to funding liquidity risk and, thus, demand more immediacy across borrowing, lending, tenors, and collateral baskets. This increases the funding costs of these banks.

[Figure 7 around here.]

5.3 Bounding the effect of unobservable variables

In this subsection, we use the methodology of Oster (2019) to bound the potential bias in our estimate of the liquidity risk markup arising from unobserved variables not included in our regression. While the previous subsections focus on credit risk, preferred habitat, and collateral holdings, the approach of Oster (2019) allows us to more generally address the concern that the liquidity risk markup might be related to something else than liquidity risk.

The method is implemented by quantifying the liquidity risk markup in a one-step approach by regressing funding cost on the market order share with and without controls. From the estimated coefficients and R-squares, we can derive bounds on any omitted variable bias by making assumptions about the importance of omitted variables relative to observed variables, δ, and the R-squared from a hypothetical regression of the funding cost on both observed and unobserved controls, R^2_{max}. We follow the recommendations of Oster (2019) and choose $\delta = 1$ and $R^2_{max} = 1.3\tilde{R}$, where $\tilde{R}$ is the R^2 from our regression including all controls. These assumptions are conservative as they imply that potential unobserved variables are equally important as observed variables. In fact, it is extremely unlikely that omitted variables explain more than the variables included in the model because (i) the market structure rules out many potential omitted variables and (ii) various (observable) controls motivated by the literature are already included.

Table 10 presents the results. The liquidity risk markup estimated in a one-step regression of funding cost on the share of market orders is 2.0 basis points with controls and 1.4 basis points without any controls. Using these coefficients, the corresponding R-squares and the assumptions about δ and R^2_{max}, we compute the interval for the liquidity risk markup which is shown in Column

(3). If there were unobserved variables that are equally important as all the observed variables and fixed effects already included in our model, the borrower markup would still be close to our original estimate of 2 basis points and lie in the interval between 1.4 and 2.3 basis points. Only in the completely unrealistic scenario that unobserved variables were 24 times more important than all observed controls and fixed effects in our model, the interval would include zero, such that we would conclude that our estimated liquidity risk markup is driven by something other than liquidity risk.

In Panel (b) of Table 10 we report the bounds for different values of R^2_{max}, ranging from 0.25 to 0.40. These R-squares are large in light of the fact that we are trying to explain daily data which is typically noisy. For comparison, Furfine (2001) achieves a maximum R^2 of 0.2 in his regression model for interest rates in the U.S. unsecured interbank market. Even in the most conservative case choosing $R^2_{max} = 0.4$, the borrower markup is in the interval 1.4 to 3.0 basis points, that is, still positive and close to our original estimate. Overall, the results show that our quantification of the borrower markup is robust to the presence of unobservable omitted variables.

6. Policy implications

Our findings have implications for banks, regulators, academia, and monetary policy. First, for individual banks, our results emphasize the importance of sophisticated liquidity management. Since it is costly to demand immediacy following liquidity shocks, banks must account for these additional costs in their business decision—for example, through liquidity transfer pricing. Quantifying the cost of funding immediacy enables banks to understand the trade-off between larger liquidity buffers and the need to be more aggressive to obtain funding. Thus, the findings from our paper can help to build a sounder practice for the management of liquidity risk, as stressed in IOSCO (2012). Specifically, our measure should support banks in setting up adequate systems and procedures for timely identifying, measuring, and monitoring liquidity risks.

Second, accounting for the aggregate level of the funding liquidity risk markup is important for academics examining interest rate spreads in short-term funding markets. We show that not only premiums demanded by lenders determine these spreads, but also markups paid by borrowers due to liquidity risk. Neglecting the role of borrowers could bias the interpretation of empirical results related to interest rate spreads.

Third, for policymakers, aggregate measures of the funding liquidity risk markup can serve as an indicator of market-wide liquidity stress and effectiveness of policy measures. Commonly used measures for liquidity stress such as Libor-OIS or TED spreads are no pure measure of (funding) liquidity risk, but bundle various kinds of risks including credit risk and rollover risk. As a consequence, the Libor-OIS spread can give misleading signals about liquidity risk. To show this, we construct an aggregate measure of funding liquidity risk based on our methodology and compare it to the Libor-OIS. A simple way to obtain such a measure is to compute the funding cost differential between banks with high and low liquidity risk, that is, the difference between the upper and lower rates in Panel B of Figure 1.

Figure 8 shows the evolution of our aggregate measure compared to the Libor-OIS spread and the excess liquidity in the Eurosystem, which captures the overall liquidity and monetary conditions. While both the Libor-OIS spread and our measure are high during the global financial crisis, only our measure exhibits a coherent pattern over the entire sample period. For instance, our measure increases at the height of the European sovereign debt crisis in 2011 when excess liquidity is relatively low; but it subsequently decreases in response to the ECB liquidity provisions such as the ECB's long-term refinancing operations (LTROs). In contrast, the Libor-OIS spread remains at low levels from 2010 on.

[Figure 8 around here.]

Fourth, cross-sectional differences in the funding liquidity risk markup reveal *who* has a liquidity need or surplus. This is relevant for policy makers, but also for market infrastructure providers such as exchange systems and related clearing houses. For policy makers, it facilitates distinguishing between insolvent and illiquid banks, which is important as both require different policy responses. For clearing houses, assessing clearing members' liquidity risk may help prevent negative consequences such as disorderly liquidation of collateral assets and contagion across firms. Measuring individual banks' funding liquidity risk markups helps identify and monitor banks that are prone to funding shocks on a daily basis, which is not feasible with existing bank-level measures that rely on (annual) balance sheet data. Moreover, our measure is market-based, meaning that we do not need structural assumptions, e.g., at which weights assets and liabilities of any kinds and maturities translate into cash.

Understanding cross-sectional differences in the funding liquidity risk markup is also crucial for central banks as heterogeneous funding costs adversely affect the pass-through efficiency of monetary policy. Internal operations, such as liquidity transfer pricing and funding value adjustments, create a channel through which inefficient liquidity management impacts investment decisions, pricing, and loan extensions. Therefore, banks may pass-through the differences in funding costs to their clients, such that heterogeneity spreads outside funding markets.

7. Conclusion

We propose and test the funding liquidity risk channel, which posits that borrowers with high liquidity risk are willing to pay a markup to lock in their funding. On this account, liquidity risk is factored into short-term interest rates via the borrowing side rather than the lending side, as in the mainstream view and literature. Borrowers with high liquidity risk are willing to pay, on average, two basis points more on a given day than their low-risk peers. This corresponds to an increase in nominal funding costs of over 2.5% for an increase in liquidity risk by one standard deviation. We also reveal that liquidity risk differs systematically and persistently across banks, thereby leading to systematic and persistent heterogeneity in funding costs. Our findings complement the existing literature on short-term interest rates, which emphasizes the role of lenders by examining the premiums they require as compensation for credit and market liquidity risk.

Further, we are able to quantify the funding liquidity risk markup by exploiting the market design of the euro interbank repo market. However, it seems likely that our results have external validity for other short-term debt markets. Unfortunately, there is a lack of order submission data for these markets. For example, data on unsecured money markets in Europe and the United States usually come from settlement data, which do not provide information about order submissions. Even trade repository data and data collected due to new regulatory initiatives—for example, EMIR for derivatives—do not provide this information. Given the importance of liquidity risk, this calls for an expansion of reporting requirements. The investigation of the magnitude of borrower markups in other funding markets is a subject for future research.

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Appendix

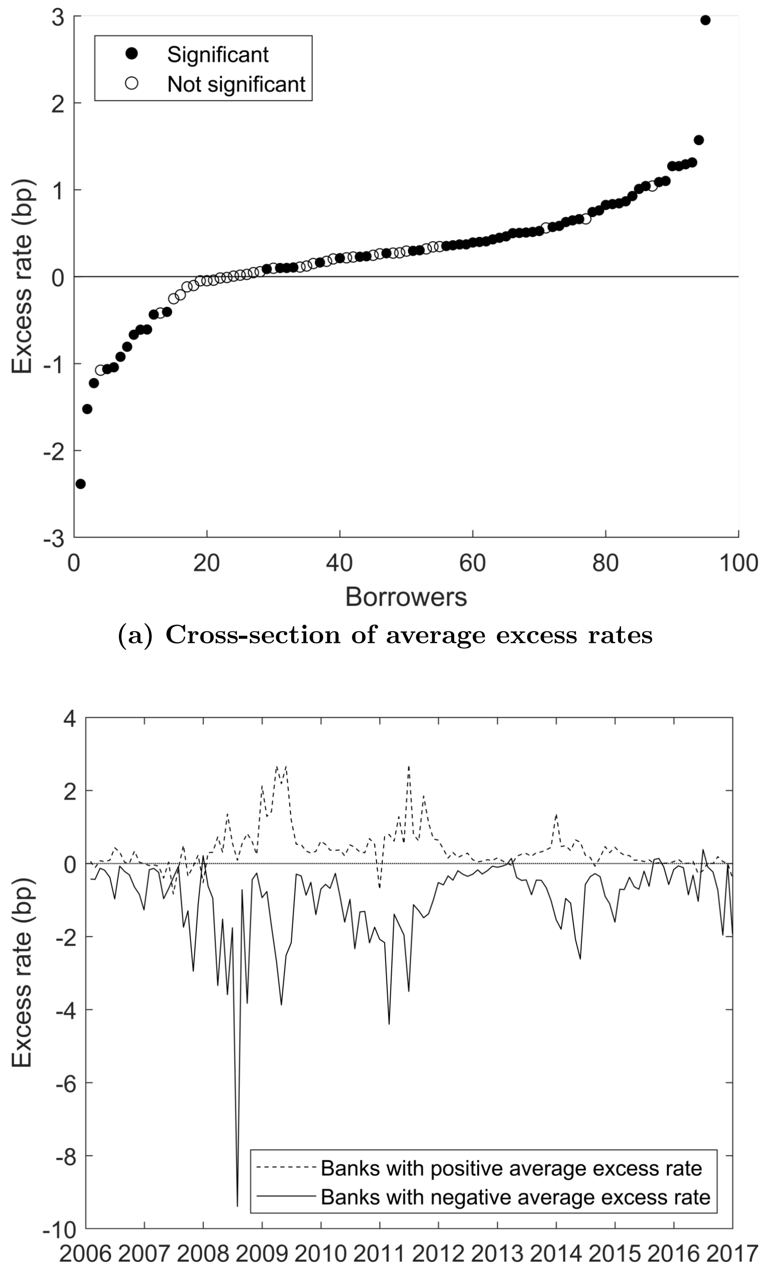
Table A.1: Variable descriptions

Table A.1 describes the variables used in the regression analysis.

Variable	Description	Frequency	Source
Excess rate	Repo rate over the daily volume-weighted average (in basis points)	daily	Eurex Repo
RF	Relative frequency of having a positive excess rate	daily	Eurex Repo
LiquidityRisk	Proxy for banks' idiosyncratic funding liquidity risk	daily	Eurex Repo
Volume	Trading volume (in million EUR)	daily	Eurex Repo
TradeTime	Volume-weighted average trading time (in decimals)	daily	Eurex Repo
Experience	Cumulated number of trading days	daily	Eurex Repo
TotalAssets	Size of total assets (in billion EUR)	yearly	SNL Financial
ROAA	Return on average assets (in decimals)	yearly	SNL Financial
Leverage	Debt-to-equity ratio (in decimals)	yearly	SNL Financial
CDS	CDS spreads (in EUR)	daily	Bloomberg

Figure 1: Heterogeneous funding costs

Panel (a) of Figure 1 presents for each borrower the average daily overnight repo rate paid in excess of the volume-weighted market average rate. In other words, it shows the average additional borrowing costs paid by each bank compared to the market average. Banks on the x-axis are ordered according to their performance. The filled black circles denote statistical significance at the 5% level. One outlier at 8.4 basis points is omitted. Panel (b) depicts the time variation of the banks with a significant positive and negative average excess rate, that is, those above and below the solid vertical line in Panel (a).



(a) Cross-section of average excess rates

(b) Excess rates of banks with positive and negative average excess rates

Figure 2: Funding liquidity risk channel intuition

Figure 2 shows the average market order shares and funding costs for banks with high and low funding liquidity risk. The black (grey) bars illustrate average market order shares and funding costs of bank-year observations with funding liquidity risk above (below) the median. We measure funding liquidity risk via the share of short-term (less than one year) wholesale over total wholesale funding. We measure funding costs as the relative frequency of paying a positive excess rate. More precisely, a relative frequency of 0.5 implies that banks pay more than the daily volume-weighted average repo rate in 50% of their trades. In our empirical analysis, we mainly use the excess rate directly as a measure for funding cost. For illustrative purposes, the relative frequency is better suited here because it is between 0 and 1 by construction. We introduce this measure more thoroughly in our empirical analysis.

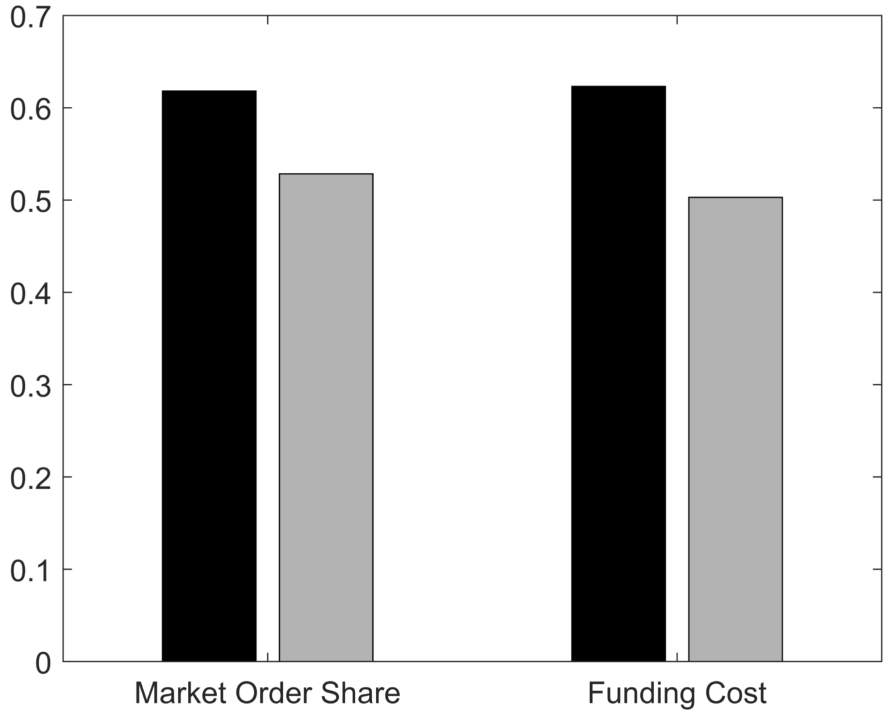
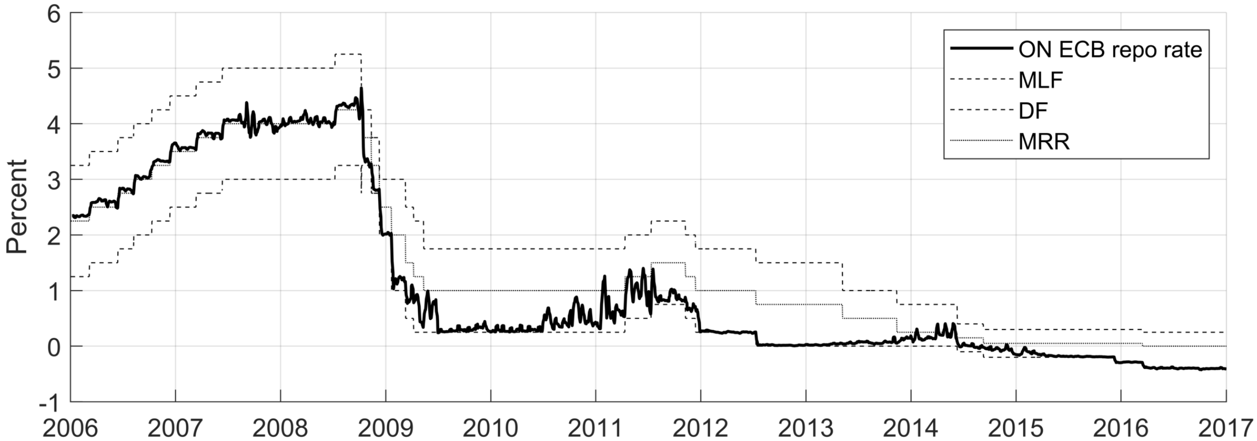
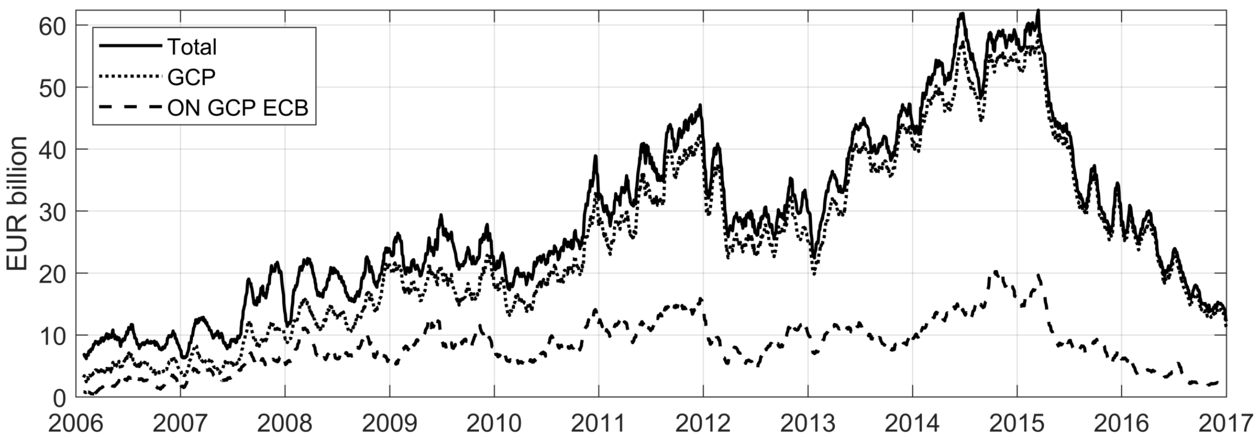


Figure 3: ECB policy rates, repo rates, and repo market volume

Panel (a) of Figure 3 shows the ECB interest rate corridor. The deposit facility (DF) and marginal lending facility (MLF) form the floor and ceiling of the corridor with the main refinancing rate (MRR) in between. The solid black line depicts the rate on ON repos with collateral from the GC Pooling ECB basket. Panel (b) shows the total repo volume at Eurex Repo (solid line), the total GC Pooling repo volume (dotted line), and the ON repo volume with collateral from the GC Pooling ECB basket (dashed line).



(a) ECB interest rate corridor and ON ECB repo rate



(b) Repo volume

Figure 4: Daily net-to-gross ratios

Figure 4 shows the distribution of daily net-to-gross ratios. The net-to-gross ratio is defined as net borrowing (i.e., borrowing − lending) over total borrowing and lending (i.e., borrowing + lending). A net-to-gross ratio of 1 indicates that a bank only borrows on a given day. Correspondingly, a ratio of −1 indicates pure lending. The figure includes trades from all GC baskets and tenors at Eurex. Hence, it captures trading across baskets and tenors.

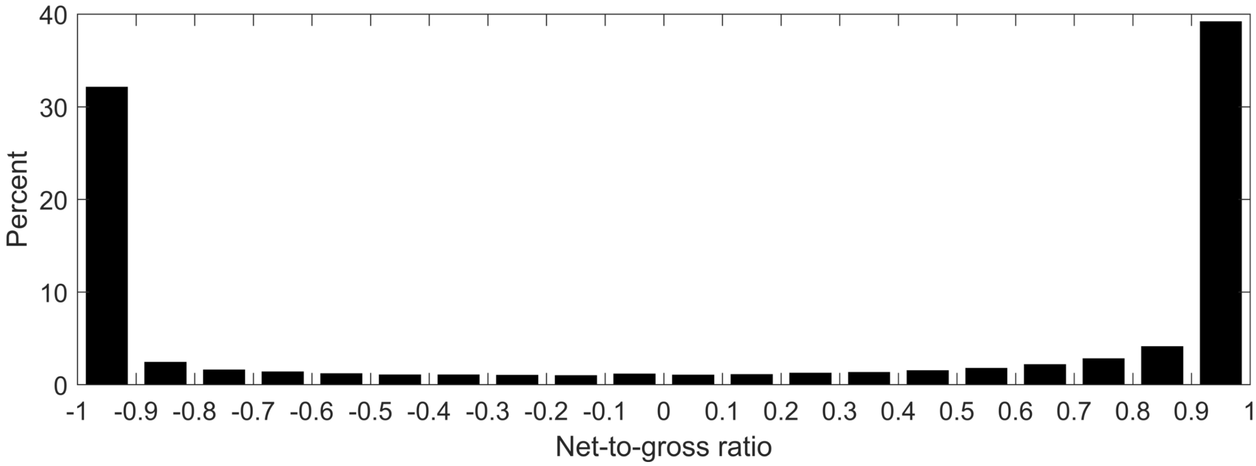


Figure 5: Heterogeneous funding costs (relative frequencies)

Figure 5 presents for every borrower the relative frequency, RF, of having a positive excess rate. In other words, it shows the proportion of trades in which each borrower pays more than the daily volume-weighted average repo rate. Banks on the x-axis are ordered according to their performance. The filled black circles denote statistical significance at the 5% level. A relative frequency of 0.5 implies that a borrower pays more than average in 50% of its trades. This figure is similar to Panel (a) of Figure 1, but it is robust to outliers because RF is between 0 and 1 by construction.

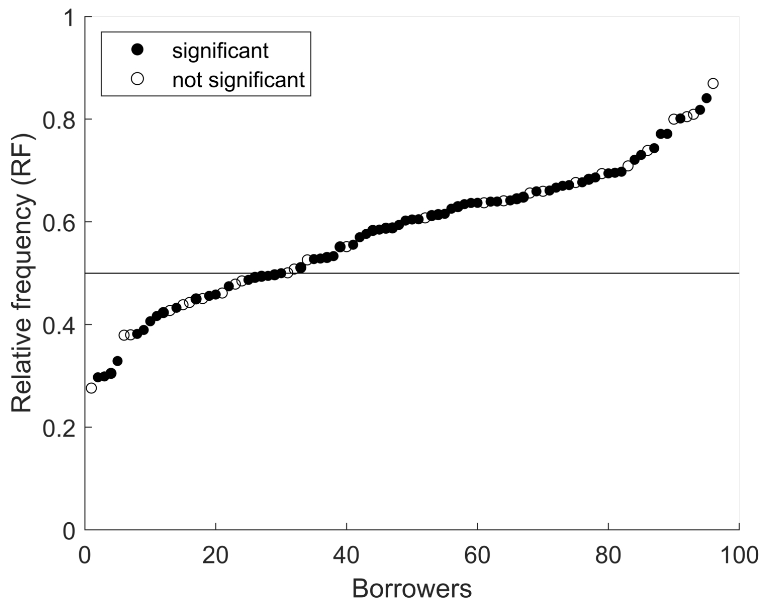


Figure 6: Heterogeneous funding costs (lenders)

Figure 6 presents for each lender the average daily repo rate received in excess of the average volume-weighted market rate. In other words, it shows the average additional return from lending compared to the market average. Banks on the x-axis are ordered according to their performance. The filled black circles denote statistical significance at the 5% level.

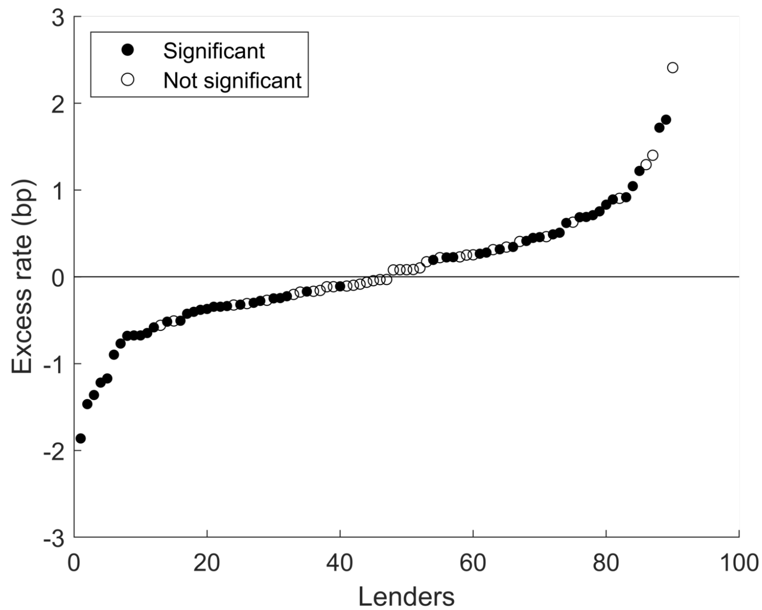
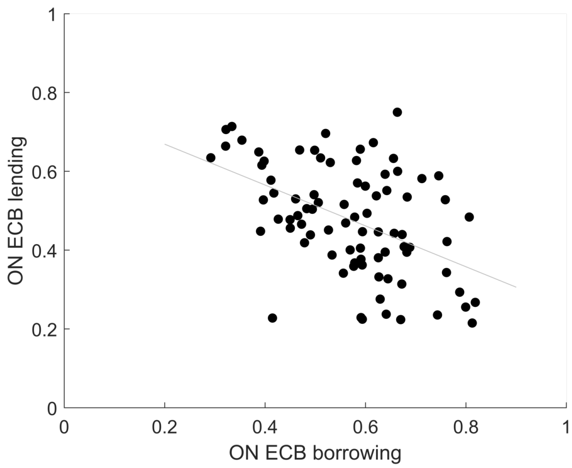
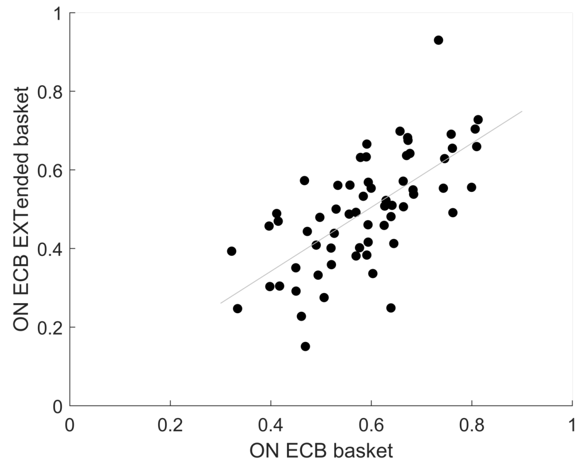


Figure 7: Performance across borrowing, lending, and collateral baskets

Panel (a) of Figure 7 presents the performance of banks across borrowing and lending and Panel (b) across the ECB and the riskier ECB EXTended basket. The relative frequency of banks is used as the performance measure. It ranges from 0 to 1; a value of 0.5 means a bank pays more than the daily average repo rate in 50% of its trades. Every dot represents one bank. Outperforming the market means having a relative frequency greater than 0.5 when borrowing and smaller 0.5 when lending.



(a) Performance across borrowing and lending



(b) Performance across collateral baskets

Figure 8: Aggregate measure of the funding liquidity risk markup

Figure 8 compares an aggregate measure of the funding liquidity risk markup (solid line) with the Libor-OIS spread (dashed line). Our aggregate measure is constructed as the 20-day moving average of the funding cost differential between banks with high and low liquidity risk. For comparison, the figure also includes aggregate excess reserves in the Eurosystem, which are defined as deposits at the ECB deposit facility net of the recourse to the marginal lending facility, plus current account holdings in excess of those contributing to the minimum reserve requirements.

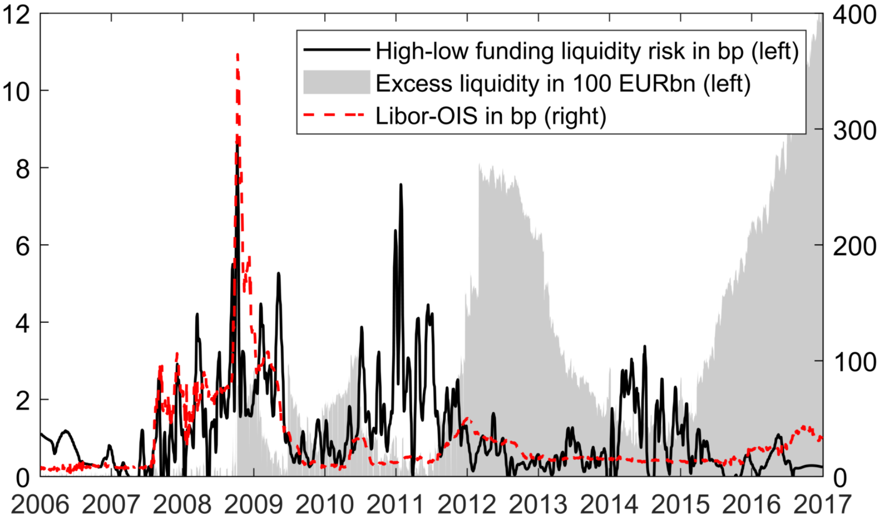


Table 1: Execution probabilities

Table 1 presents the execution probabilities for limit orders posted by borrowers.

$P_t^k(b) = 0$	if $b < \hat{b}_{t+1}^H$
$P_t^k(b) = \frac{1}{2}\theta\tau^k$	if $\hat{b}_{t+1}^H \leq b < \hat{b}_{t+1}^L$
$P_t^k(b) = \frac{1}{2}\theta\tau^k + \frac{1}{2}(1-\theta)\tau^k = \frac{1}{2}\tau^k$	if $\hat{b}_{t+1}^L \leq b$

Table 2: Order submission strategy of high and low liquidity risk banks

Table 2 summarizes the order submission strategies of high- and low-liquidity-risk banks for all relevant scenarios. The first two columns show the type of bank that is arriving to the market and the state of the order book at the time of arrival. The third column highlights the preferred order type and the fourth column depicts the rates between which the bank is indifferent.

Arriving bank	State of order book	Order type	Interest rate
H borrower	$\hat{a}^H$	Indifferent	$\hat{a}^H$, $\hat{b}^H$ or $\hat{b}^L$
	$\hat{a}^L$	Market order	$\hat{a}^L$
H lender	$\hat{b}^H$	Indifferent	$\hat{b}^H$, $\hat{a}^H$ or $\hat{a}^L$
	$\hat{b}^L$	Market order	$\hat{b}^L$
L borrower	$\hat{a}^H$	Limit order	$\hat{b}^H$ or $\hat{b}^L$
	$\hat{a}^L$	Indifferent	$\hat{a}^L$, $\hat{b}^H$ or $\hat{b}^L$
L lender	$\hat{b}^H$	Limit order	$\hat{a}^H$ or $\hat{a}^L$
	$\hat{b}^L$	Indifferent	$\hat{b}^L$, $\hat{a}^H$ or $\hat{a}^L$

Table 3: Summary statistics

Table 3 presents summary statistics for the daily repo data and the yearly balance sheet data. NT is the number of bank-day observations and N is the number of banks. Balance sheet data is not available for all banks. Trade time is the time of the day in decimals. For example, 13.5 means 1.30 pm. The number of bank-day observations is higher for Experience because we assume any repo trade (not only ON repos from the ECB basket) to increase the experience of a bank.

Panel (a): Repo panel data (daily)

	Mean	Median	Std	Min	Max	NT	N
Excess rate (bp)	−0.05	0.04	2.96	−69.07	75.41	37,346	95
Excess rate (rel. frequency)	0.53	0.59	0.45	0.00	1.00	37,346	95
Market order share	0.53	0.59	0.45	0.00	1.00	37,346	95
Volume	617	320	817	1	12,425	37,346	95
Trade time	12.38	12.28	2.33	5.91	17.00	37,346	95
Number of trades	2.56	2.00	2.43	1	42	37,346	95
Experience	699	554	566	1	2,703	90,955	95

Panel (b): Balance sheet panel data (yearly)

	Mean	Median	Std	Min	Max	NT	N
Total assets (EURbn)	329	87	583	1	3,544	590	63
ROAA	0.20	0.21	0.65	−6.44	3.15	560	63
Leverage	6.13	4.31	6.21	0.00	40.51	538	58
Short/total funding	0.66	0.69	0.25	0.04	1.00	421	41
Short/long funding	54	2	556	0	8,535	421	41
Non-liquid/total assets	0.55	0.57	0.21	0.02	1.00	425	47
CDS	136	115	110	1	679	216	25

Table 4: Summary statistics of *LiquidityRisk*

Table 4 presents summary statistics for *LiquidityRisk*, our measure for banks' idiosyncratic funding liquidity risk. The first row captures the full sample. The second and third rows examine the statistics for banks with high and low funding costs. Banks with high (low) funding costs are defined as having a positive (negative) average excess rate over the full sample. In the fourth and fifth row, we link *LiquidityRisk* to the balance sheet proxy for funding liquidity risk, which we have used in Figure 2 in Section 3.1: the share of short-term wholesale funding of banks.

Panel (a): Repo panel data (daily)

LiquidityRisk	Mean	Median	Std	Min	Max	NT
Total	0.00	−0.03	0.42	−0.87	0.88	11,486
High funding costs	0.06	0.14	0.42	−0.87	0.88	6,933
Low funding costs	−0.09	−0.26	0.40	−0.76	0.83	4,553

Panel (b): Balance sheet panel data (yearly)

LiquidityRisk	Mean	Median	Std	Min	Max	NT
High share ST wholesale	0.03	0.09	0.27	−0.74	0.46	118
Low share ST wholesale	−0.01	0.02	0.24	−0.74	0.41	118
High share ST deposits	0.11	0.12	0.22	−0.52	0.46	46
Low share ST deposits	0.01	−0.04	0.26	−0.66	0.39	46

Table 5: Validity test of *LiquidityRisk*: Logistic regression

Table 5 presents the results of a logistic regression of *LiquidityRisk* > 0 on *Switch*. The former is a binary variable that becomes 1 when *LiquidityRisk* is positive. *Switch* is a dummy that takes the value 1 on days when a bank enters the market as lender and later switches to borrowing. The stars ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	LiquidityRisk > 0	Odds Ratio
Switch	0.820^{***}	2.271^{***}
	(11.53)	(11.53)
Constant	-0.248^{***}	
	(-23.72)	
N	38,003	38,003

Table 6: Validity test of *LiquidityRisk*: End-of-maintenance period

Table 6 summarizes the differences in liquidity risk of borrowers at the end of the maintenance period compared to all other days of the period. t indicates the last day of the maintenance period, $t-1$ and $t-2$ the two preceeding days. The numbers in bold are repo contracts that provide funding on the last day of the maintenance period. The stars ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	t	$t-1$	$t-2$
ON	**0.033*****	-0.023^{***}	-0.041^{***}
TN	0.032^{**}	**0.123*****	-0.001
SN	0.004	0.063^{***}	**0.112*****

Table 7: Liquidity risk and funding costs (panel regression)

Columns (1) to (3) of Table 7 present the results of the baseline two-stage regression analysis with the first stage in Column (1) and the second stage in Columns (2) and (3). Columns (4) and (5) show the results of a subsample analysis for the financial crisis and times of high levels of excess liquidity, which we call floor system. "Financial crisis" is defined as the Global Financial Crisis (1 July 2007 – 31 July 2009). "Floor system" is defined as the time after the allotment of the two major LTROs around the beginning of 2012 (1 January 2012 – 31 Dec 2016). It also includes the ECB's quantitative easing. Funding costs are measured by the daily excess repo rate in basis points. $LiquidityRisk$ is our proxy for the idiosyncratic funding liquidity risk of banks, as presented in Section 4.3. All models are estimated via least square dummy variable (LSDV) regressions, including bank and day fixed effects. $Experience$ is measured by the cumulative number of trading days in logs. $Volume$, $TotalAssets$, and CDS spreads are also in logs. t-statistics are shown in parentheses. The stars ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Baseline			Crisis	Floor
	(1)	(2)	(3)	(4)	(5)
	MOS	r^e	r^e	r^e	r^e
$LiquidityRisk$		1.915^{***}	2.005^{***}	2.712^{***}	1.005^{***}
		(9.22)	(10.62)	(9.85)	(7.69)
Volume	-0.0641^{***}		0.124^{*}	0.675^{***}	-0.0490
	(-6.56)		(1.79)	(5.22)	(-0.98)
TradeTime	-0.0102		-0.327^{***}	-0.433^{***}	-0.0377
	(-1.02)		(-9.50)	(-3.28)	(-1.33)
Experience	0.0292		-0.0683	-0.702	0.0358
	(1.66)		(-0.36)	(-1.49)	(0.32)
TotalAssets	0.0495		1.493	-0.0265	0.0978
	(1.36)		(1.42)	(-0.03)	(0.10)
ROAA	-0.0324		0.158	0.0287	0.426
	(-0.95)		(1.21)	(0.16)	(1.52)
Leverage	-0.00415		0.0182	0.00286	0.00844
	(-1.34)		(0.75)	(0.15)	(0.14)
CDS	0.0172		0.00631	-0.222	0.331
	(0.95)		(0.11)	(-1.28)	(1.39)
Constant	0.455^{*}	-0.184^{***}	-5.590	5.291	-1.926
	(1.93)	(-158.30)	(-0.89)	(0.86)	(-0.35)
Bank/Day FE	no/no	yes/yes	yes/yes	yes/yes	yes/yes
NT	11,486	11,486	11,486	2,207	4,591
R^2	0.0600	0.236	0.267	0.288	0.432
Adj. R^2	0.0594	0.0368	0.0758	0.0576	0.275

Table 8: Robustness checks

Table 8 presents the results of our robustness checks. In Column (1), we employ the two-step Arellano-Bond dynamic panel estimator with Windmeijer error corrections. All explanatory variables are instrumented by their first lag. To keep the total number of instruments small, the GMM moment conditions are limited to five lags lags. In Column (2), we use the relative frequency of having a positive excess rate, RF, as dependent variable. Columns (3) and (4) replicate the regression results of our main model using tomorrow-next (TN) and spot-next (SN) repos as well as collateral from the riskier ECB EXTended basket. $LiquidityRisk$ is our proxy for the idiosyncratic funding liquidity risk of banks, as presented in Section 4.3. $Experience$ is measured by the cumulative number of trading days in logs. $Volume$, $TotalAssets$, and CDS spreads are also in logs. t-statistics are shown in parentheses. The stars ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) r^e	(2) RF	(3) TN/SN	(4) ECB EXT
$LiquidityRisk$	2.245***	0.381***	0.870***	2.054***
	(5.76)	(17.43)	(8.36)	(7.84)
r^e_{t-1}	0.0809**			
	(2.08)			
Constant		−0.305	−1.962	−2.209
		(−0.36)	(−0.56)	(−0.26)
Controls	yes	yes	yes	yes
Bank/Day FE	yes/yes	yes/yes	yes/yes	yes/yes
NT	8,599	11,486	7,720	3,519
Adj. R^2		0.252	−0.0320	0.0990
Instruments	18			
AR(1) p-value	0.00601			
AR(2) p-value	0.966			
Hansen p-value	0.255			

Table 9: Omitted variables

Table 9 presents results of three robustness checks that address concerns about credit risk being an omitted variable. Columns (1) and (2) present the first- and second-stage results when using first-differences of CDS spreads to control for credit risk instead of levels. Columns (3) and (4) show results on a subsample analysis where we drop all observations two weeks before and after a change in banks' Standard & Poor's credit ratings. Finally, Columns (5) and (6) present the results of the lender regression. *LiquidityRisk* is our proxy for the idiosyncratic funding liquidity risk of banks, as presented in Section 4.3. *Experience* is measured by the cumulative number of trading days in logs. *Volume*, *TotalAssets*, and *CDS* spreads are also in logs. t-statistics are shown in parentheses. The stars ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Δ CDS		Subsample		Lender	
	(1)	(2)	(3)	(4)	(5)	(6)
	MOS	r^e	MOS	r^e	MOS	r^e
LiquidityRisk		2.009***		1.970***		−1.851***
		(10.67)		(9.78)		(−7.94)
Δ CDS	-0.0464	0.828				
	(-1.17)	(1.56)				
CDS			0.0191	0.00487	0.0456	0.205
			(1.08)	(0.09)	(1.39)	(1.29)
Constant	0.554*	-5.172	0.490*	-6.400	0.645*	1.920
	(1.80)	(-0.86)	(2.03)	(-1.02)	(2.11)	(0.22)
Controls	yes	yes	yes	yes	yes	yes
Bank/Day FE	no/no	yes/yes	no/no	yes/yes	yes/yes	yes/yes
NT	11,485	11,485	10,418	10,418	4,861	4,861
R^2	0.0587	0.268	0.0606	0.295	0.149	0.414
Adj. R^2	0.0581	0.0763	0.0600	0.0985	0.148	0.106

Table 10: Bounding the effect of unobservable variables

This table presents results of the analysis of the potential effect of omitted variables on the estimated liquidity risk markup, β, using the methodology of Oster (2019). Panel (a) shows the one-step regression results for the parameter choices recommended by Oster (2019): $\delta = 1$ and $R_{max} = 0.31$. This parameter choice is conservative as it implies that potential unobserved variables are equally important as observed variables. Column (1) shows the baseline regression results without control variables ($r^e_{i,t} = \beta\ MOS_{i,t} + \varepsilon_{i,t}$). Column (2) presents the results when including the full set of control variables ($r^e_{i,t} = \beta\ MOS_{i,t} + X_{i,t}\ \theta + \eta_i + \lambda_t + \varepsilon_{i,t}$). Column (3) shows the main result of the analysis, i.e., the identified set of values for the funding liquidity risk markup when allowing for potential omitted variables. Column (4) shows the value of δ which would lead an identified set so large that it includes $\beta = 0$ given $R_{max} = 0.31$. All results are computed using the Stata package psacalc. In Panel (b) we repeat the analysis for different plausible values of R_{max} based on the previous literature, ranging from 0.25 to 0.40.

Panel (a)

	(1) Uncontrolled	(2) Controlled	(3) Identified set	(4) δ for $\beta = 0$
β	1.431***	2.005***	[1.431;2.337]	24.08
	(18.64)	(10.12)		
NT	11,486	11,486		
R^2	0.029	0.240		

Panel (b)

	$R_{max} = 0.25$	$R_{max} = 0.30$	$R_{max} = 0.35$	$R_{max} = 0.40$
Identified set	[1.431;2.045]	[1.431;2.282]	[1.431;2.587]	[1.431;2.986]
δ for $\beta = 0$	55.17	26.58	17.51	13.05

Internet Appendix for
"Liquidity Risk and Funding Cost"

August 31, 2020

This supplemental appendix extends the results in the main paper by presenting additional analyses and robustness checks.

IA.1. Funding liquidity risk channel: Motivation

According to the funding liquidity risk channel, higher funding liquidity risk should lead to a higher demand for immediacy as well as higher funding cost. Table IA.1 presents the results of two pooled panel regressions using yearly repo and balance sheet panel data that provide empirical evidence for this link. We proxy the funding liquidity risk of banks via their reliance on short-term wholesale funding. More precisely, we compute the share of short-term (less than one year) over total wholesale funding. We measure funding costs as the relative frequency of having a positive excess rate RF. A relative frequency of 0.5 implies that banks pay more than the daily volume-weighted average repo rate in 50% of their trades. This measure is robust to outliers and by construction between 0 and 1. We introduced it in Section 4.4.3.

In line with the funding liquidity risk channel, Column (1) of Table IA.1 shows that a 10% increase in the share of short-term wholesale funding leads to a 2.1% increase in the market order share of banks and a 2.3% increase in funding cost, meaning the probability of paying more than the volume-weighted market average increases by 2.3%.

Table IA.1: Pooled panel regression

Table IA.1 presents the results of two pooled panel regressions. We use the share of short-term (less than one year) over total wholesale funding as a proxy for funding liquidity risk. Funding cost is measured as the relative frequency of having a positive excess rate RF, introduced in Section 4.4.3. The stars ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Market order share	(2) Funding Cost
Share ST wholesale funding	0.210***	0.228***
	(2.60)	(3.46)
Constant	0.457***	0.436***
	(9.68)	(11.26)
N	236	236
R^2	0.0318	0.0567
R^2_{adj}	0.0277	0.0527

IA.2. Model derivations

In this section, we provide further derivations for the model presented in Section 3.2. First, we derive the cut-off rates for lenders. The cut-off rate $\hat{b}_t^k$ that makes a lender of type k indifferent between using a market or a limit order solves:

$$E_t\left[\pi(a_t^*)\right] = \pi(\hat{b}_t^k) \tag{IA.20}$$

$$P_t^k(a_t^*)\left[a_t^* - \mu_0 - v\right] + \Big(1 - P_t^k(a_t^*)\Big)\left[r_{DF} - \mu_0 - v\right] = \hat{b}_t^k - \mu_0 - v, \tag{IA.21}$$

where the left-hand side is the expected profit from posting a limit order at a_t^* and the right-hand side is the profit of using a market order that is executed immediately at $\hat{b}_t^k$. Solving for the cut-off borrowing rate $\hat{b}_t^k$ yields Equation (6) in the paper. The execution probabilities for the lender are presented in Table IA.2.

Table IA.2: Execution probability lender

$P_t^k(a) = 0$	if $a > \hat{a}_{t+1}^H$
$P_t^k(a) = \frac{1}{2}\theta\tau_k$	if $\hat{a}_{t+1}^L > a \geq \hat{a}_{t+1}^H$
$P_t^k(a) = \frac{1}{2}\theta\tau_k + \frac{1}{2}(1-\theta)\tau_k = \frac{1}{2}\tau_k$	if $\hat{a}_{t+1}^L \geq a$

In order to derive the equilibrium rates, we need to solve the following equations for bid and ask rates, which follow from Equations (5) – (7) in the paper:

$$\hat{a}^H = P^H(\hat{b}^H)\hat{b}^H + \Big(1 - P^H(\hat{b}^H)\Big)\, r_{MLF} = P^H(\hat{b}^L)\hat{b}^L + \Big(1 - P^H(\hat{b}^L)\Big)\, r_{MLF}$$

$$\hat{b}^H = P^H(\hat{a}^H)\hat{a}^H + \big(1 - P^H(\hat{a}^H)\big)\, r_{DF} = P^H(\hat{a}^L)\hat{a}^L + \big(1 - P^H(\hat{a}^L)\big)\, r_{DF}$$

$$\hat{a}^L = P^L(\hat{b}^H)\hat{b}^H + \Big(1 - P^L(\hat{b}^H)\Big)\, r_{MLF} = P^L(\hat{b}^L)\hat{b}^L + \Big(1 - P^L(\hat{b}^L)\Big)\, r_{MLF}$$

$$\hat{b}^L = P^L(\hat{a}^H)\hat{a}^H + \big(1 - P^L(\hat{a}^H)\big)\, r_{DF} = P^L(\hat{a}^L)\hat{a}^L + \big(1 - P^L(\hat{a}^L)\big)\, r_{DF}$$

Next, we solve for $\hat{a}^H$, $\hat{b}^H$, $\hat{a}^L$, and $\hat{b}^L$ to obtain Equations (8) – (11) in the paper.

$$\begin{aligned}
\hat{a}^H &= \frac{\tau_H\theta}{2}\left(\frac{\tau_H\theta}{2}\hat{a}^H + \left(1-\frac{\tau_H\theta}{2}\right)r_{DF}\right) + \left(1-\frac{\tau_H\theta}{2}\right)r_{MLF} \\
&= \frac{\tau_H^2\theta^2}{4}\hat{a}^H + \frac{\tau_H\theta}{2}r_{DF} - \frac{\tau_H^2\theta^2}{4}r_{DF} + \left(1-\frac{\tau_H\theta}{2}\right)r_{MLF} \\
&= \frac{1}{1-\frac{\tau_H^2\theta^2}{4}}\left(\frac{\tau_H\theta}{2}r_{DF} - \frac{\tau_H^2\theta^2}{4}r_{DF} + r_{MLF} - \frac{\tau_H\theta}{2}r_{MLF}\right) \\
&= \frac{\frac{\tau_H\theta}{2}}{1+\frac{\tau_H\theta}{2}}r_{DF} + \frac{1}{1+\frac{\tau_H\theta}{2}}r_{MLF}
\end{aligned}$$

$$\begin{aligned}
\hat{b}^H &= \frac{\tau_H\theta}{2}\left(\frac{\tau_H\theta}{2}\hat{b}^H + (1-\frac{\tau_H\theta}{2})r_{MLF}\right) + (1-\frac{\tau_H\theta}{2})r_{DF} \\
&= \frac{\tau_H^2\theta^2}{4}\hat{b}^H + \frac{\tau_H\theta}{2}r_{MLF} - \frac{\tau_H^2\theta^2}{4}r_{MLF} + (1-\frac{\tau_H\theta}{2})r_{DF} \\
&= \frac{1}{1-\frac{\tau_H^2\theta^2}{4}}\left(\frac{\tau_H\theta}{2}r_{MLF} - \frac{\tau_H^2\theta^2}{4}r_{MLF} + r_{DF} - \frac{\tau_H\theta}{2}r_{DF}\right) \\
&= \frac{\frac{\tau_H\theta}{2}}{1+\frac{\tau_H\theta}{2}}r_{MLF} + \frac{1}{1+\frac{\tau_H\theta}{2}}r_{DF}
\end{aligned}$$

$$\begin{aligned}
\hat{a}^L &= \frac{\tau_L}{2}\left(\frac{\frac{\tau_L}{2}}{1+\frac{\tau_L}{2}}r_{MLF} + \frac{1}{1+\frac{\tau_L}{2}}r_{DF}\right) + \left(1-\frac{\tau_L}{2}\right)r_{MLF} \\
&= \frac{1}{1+\frac{\tau_L}{2}}r_{MLF} + \frac{\frac{\tau_L}{2}}{1+\frac{\tau_L}{2}}r_{DF}
\end{aligned}$$

$$\begin{aligned}
\hat{b}^L &= \frac{\tau_L}{2}\left(\frac{\tau_L}{2}(b_L) + \left(1-\frac{\tau_L}{2}\right)r_{MLF}\right) + \left(1-\frac{\tau_L}{2}\right)r_{DF} \\
&= \frac{\left(\frac{\tau_L}{2}\left(1-\frac{\tau_L}{2}\right)r_{MLF}\right) + \left(1-\frac{\tau_L}{2}\right)r_{DF}}{1-\frac{\tau_L^2}{4}} \\
&= \frac{\frac{\tau_L}{2}}{1+\frac{\tau_L}{2}}r_{MLF} + \frac{1}{1+\frac{\tau_L}{2}}r_{DF}
\end{aligned}$$

Table IA.3 summarizes the cut-off prices and limit orders that banks are indifferent to paying/receiving.

In order to compute the possible bid/ask spreads, we compute all four rate combinations from

Table IA.3: Market order cut-offs and limit orders

Type	Market order cut-off	Indifferent limit orders
High borrower	$\hat{a}^H$	$\hat{b}^H$, $\hat{b}^L$
High lender	$\hat{b}^H$	$\hat{a}^H$, $\hat{a}^L$
Low borrower	$\hat{a}^L$	$\hat{b}^H$, $\hat{b}^L$
Low lender	$\hat{b}^L$	$\hat{a}^H$, $\hat{a}^L$

Equations (8) – (11) in the paper:

$$\begin{aligned}
\hat{a}^H - \hat{b}^H &= \left(\frac{\frac{\tau_H \theta}{2}}{1 + \frac{\tau_H \theta}{2}} r_{DF} + \frac{1}{1 + \frac{\tau_H \theta}{2}} r_{MLF} \right) - \left(\frac{\frac{\tau_H \theta}{2}}{1 + \frac{\tau_H \theta}{2}} r_{MLF} + \frac{1}{1 + \frac{\tau_H \theta}{2}} r_{DF} \right) \\
&= \frac{2 - \tau_H \theta}{2 + \tau_H \theta} r_{MLF} - \frac{2 - \tau_H \theta}{2 + \tau_H \theta} r_{DF} \\
&= \frac{2 - \tau_H \theta}{2 + \tau_H \theta} (r_{MLF} - r_{DF}) \\
&= \frac{4 - \tau_L \tau_H \theta + 2(\tau_L - \tau_H \theta)}{(2 + \tau_L)(2 + \tau_H \theta)} (r_{MLF} - r_{DF})
\end{aligned}$$

$$\begin{aligned}
\hat{a}^L - \hat{b}^L &= \left(\frac{1}{1 + \frac{\tau_L}{2}} r_{MLF} + \frac{\frac{\tau_L}{2}}{1 + \frac{\tau_L}{2}} r_{DF} \right) - \left(\frac{\frac{\tau_L}{2}}{1 + \frac{\tau_L}{2}} r_{MLF} + \frac{1}{1 + \frac{\tau_L}{2}} r_{DF} \right) \\
&= \frac{2 - \tau_L}{2 + \tau_L} (r_{MLF} - r_{DF}) \\
&= \frac{4 - \tau_L \tau_H \theta - 2(\tau_L - \tau_H \theta)}{(2 + \tau_L)(2 + \tau_H \theta)} (r_{MLF} - r_{DF})
\end{aligned}$$

$$\begin{aligned}
\hat{a}^H - \hat{b}^L &= \left(\frac{\frac{\tau_H \theta}{2}}{1 + \frac{\tau_H \theta}{2}} r_{DF} + \frac{1}{1 + \frac{\tau_H \theta}{2}} r_{MLF} \right) - \left(\frac{\frac{\tau_L}{2}}{1 + \frac{\tau_L}{2}} r_{MLF} + \frac{1}{1 + \frac{\tau_L}{2}} r_{DF} \right) \\
&= \left(\frac{2}{2 + \tau_H \theta} - \frac{\tau_L}{2 + \tau_L} \right) r_{MLF} - \left(\frac{2}{2 + \tau_L} - \frac{\tau_H \theta}{2 + \tau_H \theta} \right) r_{DF} \\
&= \frac{4 - \tau_L \tau_H \theta}{(2 + \tau_L)(2 + \tau_H \theta)} (r_{MLF} - r_{DF})
\end{aligned}$$

$$\begin{aligned}
\hat{a}^L - \hat{b}^H &= \left(\frac{1}{1 + \frac{\tau_L}{2}} r_{MLF} + \frac{\frac{\tau_L}{2}}{1 + \frac{\tau_L}{2}} r_{DF} \right) - \left(\frac{\frac{\tau_H \theta}{2}}{1 + \frac{\tau_H \theta}{2}} r_{MLF} + \frac{1}{1 + \frac{\tau_H \theta}{2}} r_{DF} \right) \\
&= \frac{4 - \tau_L \tau_H \theta}{(2 + \tau_L)(2 + \tau_H \theta)} (r_{MLF} - r_{DF})
\end{aligned}$$

The four spreads have different probabilities of occurrence, depending on θ:

1. $[a^H, b^H]$ arises if H bank follows H bank. The probability is θ^2.

2. $[a^L, b^L]$ arises if L bank follows L bank. The probability is $(1-\theta)^2$.

3. $[a^L, b^H] = [a^H, b^L]$ arises if L bank follows H bank or vice versa. The probability is $2(1-\theta)\theta$.

IA.3. Alternative first and second-stage regression models

Using the residuals from Equation (16) as proxy for funding liquidity risk is a conservative measure because some of the controls may capture parts of the variation in banks' funding liquidity risk. In addition, balance sheet data and CDS spreads are not available for all banks, thereby reducing the number of observations. Against this background, in this section, we test whether our results are robust to changing the composition of control variables and allowing for a bigger sample of banks.

Table IA.4 presents first- and second-stage regression results for different specifications. In Column (1) and (2), we drop CDS spreads from the matrix of control variables. This enables us to extend the number of observations to 27,801. In Column (3) and (4), we drop $TradeTime$ from the matrix of controls because it might eliminate some of the variation in liquidity risk to the extent that it captures the time of arrival of banks in the market. The later a bank arrives, the more time-sensitive a funding shock could be, as markets tend to be closing soon. However, $TradeTime$ only measures the execution time of a trade. In particular in the case of limit orders, the execution time of a trade can be far away from the market arrival of a bank. Since the execution time of trades is important—particularly for the second stage—we decide to include it in our matrix of controls in our baseline specification in the paper. In Column (5) and (6), we add bank fixed effects to the first-stage model. Bank fixed effects enable us to control for time-invariant unobserved heterogeneity. For example, there might be institutional differences across banks that affect their order choice but are unrelated to funding liquidity risk. The results remain qualitatively the same in all specifications.

Table IA.4: Alternative first- and second stage specifications

Table IA.4 presents alternative specification for the first and second stage regression models. *LiquidityRisk* is our proxy for the idiosyncratic funding liquidity risk of banks, as presented in Section 4.3. All models are estimated via least square dummy variable (LSDV) regressions, including bank and day fixed effects. *Experience* is measured by the cumulative number of trading days in logs. *Volume*, *TotalAssets*, and *CDS* spreads are also in logs. t-statistics are shown in parentheses. The stars ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) MOS	(2) r^e	(3) MOS	(4) r^e	(5) MOS	(6) r^e
LiquidityRisk		1.380***		1.957***		2.005***
		(10.82)		(9.13)		(10.62)
Volume	-0.0826***	0.0188	-0.0595***	0.290***	-0.0529***	0.146**
	(-7.06)	(0.41)	(-6.12)	(3.61)	(-10.85)	(2.14)
TradeTime	-0.00673	-0.196***			0.00772	-0.291***
	(-1.02)	(-5.75)			(1.16)	(-8.68)
Experience	0.0123	-0.110	0.0247	-0.119	0.0345*	-0.0577
	(0.92)	(-0.94)	(1.32)	(-0.56)	(1.78)	(-0.30)
Size	0.0102	0.767*	0.0524	1.471	-0.0439	1.306
	(0.80)	(1.95)	(1.37)	(1.35)	(-1.04)	(1.25)
ROAA	-0.00972	0.0920	-0.0308	0.314**	0.00105	0.225*
	(-0.43)	(1.16)	(-0.87)	(2.39)	(0.06)	(1.72)
Leverage	-0.00206	0.0278	-0.00433	0.0301	0.00119	0.0289
	(-0.51)	(1.30)	(-1.39)	(1.12)	(0.26)	(1.19)
CDS			0.0169	-0.0706	-0.0107	-0.0495
			(0.93)	(-0.89)	(-0.81)	(-0.85)
Constant	0.959***	-0.954	0.318	-9.818	0.775*	-4.951
	(5.28)	(-0.48)	(1.39)	(-1.49)	(2.07)	(-0.79)
Bank/Day FE	no/no	yes/yes	no/no	yes/yes	yes/yes	yes/yes
NT	27,801	27,801	11,486	11,486	11485	11,485
R^2	0.0533	0.197	0.0576	0.248	0.161	0.267
Adj. R^2	0.0531	0.111	0.0571	0.0513	0.159	0.0758

t statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

IA.4. Validity tests

Table IA.5 presents the contingency matrix corresponding to the logistic regression in Section 4.3.2. *LiquidityRisk* is our measure of liquidity risk and *Switch* indicates if a bank switches from lending to borrowing on a given day. We use the switching between borrowing and lending as a proxy for liquidity shocks and hence, we expect banks to have a higher liquidity risk on days when they switch. In line with this expectation, Table IA.5 shows that the likelihood of having a positive liquidity risk is considerably higher on switching days ($\frac{16{,}272}{37{,}127} = 0.44$ when $Switch = 0$ vs. $\frac{560}{876} = 0.64$ when $Switch = 1$).

Table IA.5: Validity test of *LiquidityRisk*: Contingency table

Table IA.5 presents a contingency matrix of *LiquidityRisk* when changing or not changing the direction of trading. A trade is categorized as switching ($Switch = 1$) if a bank switches from lending to borrowing.

	$Switch = 0$	$Switch = 1$	Total
$LiquidityRisk \leq 0$	20,855	316	21,171
$LiquidityRisk > 0$	16,272	560	16,832
Total	37,127	876	38,003

Table IA.6 and Table IA.7 present the contingency matrix and logistic regression results for lenders. In case of lenders, a trade is categorized as switching if a bank switches from borrowing to lending. The results are similar to borrowers. The likelihood of having a positive liquidity risk is considerably higher on switching days ($\frac{4{,}738}{12{,}241} = 0.39$ when $Switch = 0$ vs. $\frac{124}{196} = 0.63$ when $Switch = 1$). Lenders switch slightly less often than borrowers, but the odds ratio of having a positive liquidity risk increases by 2.7 if they switch.

Table IA.6: Validity test of *LiquidityRisk*: Contingency table (lender)

Table IA.6 shows a contingency matrix of *LiquidityRisk* when changing or not changing the direction of trading. A trade is categorized as switching ($Switch = 1$) if a bank switches from borrowing to lending.

	$Switch = 0$	$Switch = 1$	Total
$LiquidityRisk \leq 0$	7,503	72	7,575
$LiquidityRisk > 0$	4,738	124	4,862
Total	12,241	196	12,437

Table IA.7: Validity test of *LiquidityRisk*: Logistic regression (lender)

Table IA.7 presents the results of a logistic regression of $LiquidityRisk > 0$ on the dummy *Switch*, which takes the value 1 on days on which a bank enters the market as borrower and later switches to lending. The stars ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	$LiquidityRisk > 0$	Odds Ratio
Switch	1.003***	2.727***
	(6.72)	(6.72)
Constant	−0.460***	
	(−24.77)	
N	12,437	12,437

IA.5. Additional figures

Figure IA.1: Performance across tenors

Figure IA.1 presents the performance of banks across different tenors. The y-axis plots the relative frequency of banks when trading TN and SN repos. The x-axis plots the performance for ON repos. The relative frequency ranges from 0 to 1; a value of 0.5 means a bank pays more than the daily average repo rate in 50% of its trades. Every dot represents one bank. Outperforming the market means having a relative frequency greater than 0.5 when borrowing and smaller 0.5 when lending.