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Unsecured and Secured Funding

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ABSTRACT

We empirically investigate why wholesale funding is fragile by providing the first study of how individual banks borrow and lend in the euro unsecured and secured interbank market. Consistent with theories in which lenders enforce market discipline by monitoring counterparty credit risk and theories highlighting that secured loans are less informational sensitive, we find that banks with low credit worthiness replace unsecured borrowing with secured loans. Moreover, riskier lenders provide more secured loans to replace unsecured lending, which is not consistent with speculative or precautionary liquidity hoarding theories. Instead, lenders are precautionary in the sense that they prefer to lend against safe collateral.

KEYWORDS: Liquidity hoarding, asymmetric information, counterparty credit risk, wholesale funding fragility, interbank market

JEL CODES: E42, E43, E58, G01, G21, G28

Banks heavily rely on wholesale funding, which includes secured loans such as repurchase agreements (repo) and unsecured loans.[1] A common view among economists and policy makers is that wholesale funding is vulnerable to sudden stops, runs, rollover risk, and contagion. The U.S. subprime and European sovereign debt crises provide vivid examples of bank's liquidity dry-ups and sudden increases of wholesale funding costs. In addition to financial stability, wholesale funding is important for the real economy. For instance, interbank funding conditions can create boom and bust cycles of credits and outputs (Boissay, Collard, and Smets, 2016) and disruptions in the unsecured or secured interbank market may have different impacts on economic activity (De Fiore, Hoerova, and Uhlig, 2017). Given this importance, wholesale funding has been at the center of new regulations including liquidity requirements.[2] However, we still lack a full understanding of why wholesale funding is fragile. Moreover, it is not clear why some banks are more exposed to funding strains, and how unsecured and secured markets affect each other.

In this paper, we empirically investigate why wholesale funding is fragile. More specifically, we provide the first study on how individual banks borrow and lend in the unsecured and secured interbank market. Using unique and comprehensive bank-level data for the euro money market, we test the empirical predictions put forward by the main theories on wholesale funding fragility. In contrast with speculative and precautionary motives described in liquidity hoarding theories, we find that banks do not hoard liquidity to exploit trading opportunities or when their risk increases. Riskier banks lend less in the unsecured market, but replace unsecured loans with more secured loans, when they can lend against safe collateral. On the borrowing side, we find that banks with low credit worthiness borrow less in the unsecured market, but use more secured loans. This substitution effect is consistent with theories in which (i) lenders enforce market discipline by monitoring counterparty credit risk in the unsecured market and (ii) secured loans are less information sensitive.

Although there exists a number of theories on funding fragility, two main explanations prevail: liquidity hoarding and asymmetric information about credit risk. Liquidity hoarding entails that lenders stop lending and hold cash or central bank reserves. The motive to hoard liquidity can be speculative (e.g., Diamond and Rajan, 2011; Acharya, Gromb, and Yorulmazer, 2012; Acharya, Shin, and Yorulmazer, 2011; Gale and Yorulmazer, 2013) or precautionary, e.g., due to anticipation

[1]A repo is essentially a collateralized loan based on a simultaneous sale and forward agreement to repurchase securities at the maturity date.
[2]See, e.g.,Basel Committee on Banking Supervision (2013)

of own liquidity needs (Acharya and Skeie, 2011), high aggregate liquidity demand (Allen, Carletti, and Gale, 2009), increases in Knightian uncertainty (Caballero and Krishnamurthy, 2008; Caballero and Simsek, 2013), credit constraints and limited access to funding markets (Ashcraft, McAndrews, and Skeie, 2011), or asymmetric information on asset holdings (Malherbe, 2014; Heider, Hoerova, and Holthausen, 2015). A large share of the liquidity hoarding literature focuses on unsecured lending, implying that lenders face the tradeoff between reducing lending or liquidating assets. More recent papers introduce a secured market in which assets can be pledged. When the asset quality is sufficiently high, the aggregate amount of liquidity and its allocation are more efficient (Gale and Yorulmazer, 2013), banks hold less precautionary cash (Ahn et al., 2017), and banks can replace unsecured funding with secured funding when they lose access to the unsecured market (De Fiore, Hoerova, and Uhlig, 2017). Three empirical predictions can be derived from these theories: (i) Banks hoard more liquidity when their risk increases; (ii) Banks hoard less liquidity when they can lend against safe collateral, and (iii) Banks hoard liquidity to exploit profitable opportunities.

The second class of models focuses on asymmetric information between lenders and borrowers about the risk of the loan. The key distinguishing feature in this class of models is whether all lenders are uninformed (e.g., Stiglitz and Weiss, 1981; Freixas and Jorge, 2008; Heider, Hoerova, and Holthausen, 2015) or some lenders gain superior information about borrowers' credit risk by monitoring them (e.g., Diamond, 1984; Calomiris and Kahn, 1991; Von Thadden, 1995; Rochet and Tirole, 1996; Huang and Ratnovski, 2011). When all lenders are uninformed, they apply the same conditions to borrowers regardless of their credit quality. Thus, banks with low credit risk are disincentivized to borrow in the unsecured market because lenders overcharge them. This may lead to market breakdowns due to adverse selection as high-quality banks stop borrowing from the market. When some lenders are informed, they discriminate between high- and low-quality borrowers. When lenders become concerned about the quality of borrowing banks, the market may breakdown due to a reduction in supply in particular for low-quality banks. Thus, two contrasting predictions emerge: When all lenders are uninformed (informed), borrowers with high (low) credit worthiness borrow less in the unsecured market.

Lenders' incentives to reduce asymmetric information and their ability to monitor depend on the funding market infrastructure. For instance, collateral can protect lenders from counterparty credit risk and monitoring requires that lenders know who their counterparty is. In both the

United States and Europe, the unsecured market is a peer-to-peer, over-the-counter market in which lenders know their counterparty and are directly exposed to the borrowers credit risk. By screening and monitoring borrowers, lenders can discriminate borrowers with lower credit worthiness thereby enforcing market discipline (Calomiris, 1999; Rochet and Tirole, 1996). In contrast, secured lending is less or not information sensitive (Dang, Gorton, and Holmström, 2012; Gorton and Ordoñez, 2014) and repos can be considered safe assets as they can be valued without expensive and prolonged analysis (Gorton, 2016), and serve as a store of value (Nagel, 2016).[3] This is especially true in Europe, where the largest part of the repo market (analyzed in this paper) has a particularly resilient infrastructure (Mancini, Ranaldo, and Wrampelmeyer, 2016; Bank of International Settlements, 2017), including (i) central clearing that eliminates direct credit risk exposures between borrowers and lenders, (ii) anonymous trading impeding counterparty identification and monitoring, and (iii) safe collateral.[4] Thus, when riskier borrowers are rationed in the unsecured market, they choose to refinance in the secured market (Hoerova and Monnet, 2016). This leads us to an additional empirical prediction: borrowers with lower credit worthiness have the incentive to substitute unsecured with secured loans if they can post eligible assets.

The euro money market represent the ideal setting to comprehensively test the various predictions derived from the different theories. To our knowledge, no previous empirical study has provided a joint analysis of unsecured and secured interbank borrowing and lending. This paper fills this gap. Our data set includes data on unsecured transactions from the TARGET2 payment system that we match with data from Eurex Repo, a major CCP-based electronic trading platform for funding-driven general collateral repos.[5] We analyze transactions with a maturity of one day (overnight, tomorrow-next, and spot-next) and cover more than 87% of volume on Eurex repo and more than 60% of the total unsecured volume.

Several results emerge from our study. On the lending side, we find that banks do not reduce their total lending when their credit worthiness decrease. In addition, there is no evidence that banks hoard liquidity to earn larger profits. Interestingly, a separate analysis of unsecured and

[3]For a survey on safe assets, see Golec and Perotti (2017).

[4]This infrastructure means that in each repo contract, the final lender and borrower do not know each other and the contract is novated by the CCP, which interposes itself into the transaction becoming the borrower to every lender and vice versa. Compared to triparty repo market in the United States, another feature strengthening the European CCP-based repo is the absence of the unwind mechanism.

[5]Repo transactions are typically used for funding purposes via general collateral (GC) repos or to obtain specific securities via special repos (specials). Thus, GC repos are mainly cash driven and the collateral can be any security from a predefined basket of securities, whereas special repos are security driven; that is, collateral is restricted to a single security.

secured lending reveals a reduction of unsecured lending associated with credit risk but this reduction is offset by an increase in secured lending. Therefore, the prediction of the liquidity hoarding theory finds support when only unsecured loans are considered. However, neither precautionary nor speculative liquidity hoarding find empirical support when we jointly analyze unsecured and secured lending. Thus, a separate analysis of unsecured lending alone can be misleading. Moreover, the substitution from unsecured to secured lending is consistent with the empirical prediction from the most recent models contemplating secured lending, that is, banks hoard less liquidity when they can lend against safe collateral.

On the borrowing side, banks with higher credit risk endure funding strains in terms of quantity rationing in the unsecured market. However, these banks offset the loss in liquidity from the unsecured market by borrowing more in the secured market. This finding is consistent with theories of (heterogeneous) lenders who monitor credit quality rather than homogeneously uninformed lenders. Again, the joint analysis is more revealing than a separate analysis of unsecured and secured borrowing. Banks with lower credit risk reduce unsecured borrowing, but are able to replace this loss by more collateralized funding.

We contribute to the existing empirical literature on interbank funding by jointly analyzing unsecured, secured borrowing and lending at the bank level. The existing empirical literature focuses on individual segments of the wholesale funding market, such as the unsecured money market in the United States (Ashcraft and Duffie, 2007; Afonso, Kovner, and Schoar, 2011a), in the euro area (Brunetti, di Filippo, and Harris, 2011; Angelini, Nobili, and Picillo, 2011; Garcia-de-Andoain, Hoffmann, and Manganelli, 2014; Garcia-de-Andoain et al., 2016; Perignon, Thesmar, and Vuillemey, 2018), and in the United Kingdom (Acharya and Merrouche, 2013). Similarly, exiting papers study secured money markets in isolation, covering the United States (Gorton and Metrick, 2012; Krishnamurthy, Nagel, and Orlov, 2014; Copeland, Martin, and Walker, 2014) and Europe (Mancini, Ranaldo, and Wrampelmeyer, 2016; Boissel et al., 2017). The joint analysis of unsecured and secured money markets is crucial for determining which theory finds empirical validation. Our results suggest that liquidity hoarding models that only include unsecured funding have a hard time explaining actual banks' behaviors in secured lending. However, our results are consistent with models that allow for secured lending, such as Gale and Yorulmazer (2013) and Ahn et al. (2017). Our analysis of borrowing behavior points to the key role of informed lenders monitoring borrowers' credit worthiness.

Second, we contribute to the academic debate on market design for wholesale funding, which plays a crucial role for fragility (see, e.g., Martin, Skeie, and von Thadden, 2014a,b). Given our finding that asymmetric information between borrowers and lenders is a key determinant of market fragility, it is not clear a priori whether transparency or opaqueness is the most suitable characteristic for the wholesale funding market. On the one hand, information about the credit quality of the borrower can facilitate efficient liquidity allocation, risk sharing, and market discipline (Calomiris, 1999; Flannery and Sorescu, 1996) but may generate inefficient liquidation (Huang and Ratnovski, 2011). On the other hand, opaqueness is an underpinning feature of over-collateralized money market instruments, (Dang, Gorton, and Holmström, 2012; Holmström, 2015) but it can lead to the search for information about previously information-insensitive debt claims, thus generating financial crises (Gorton and Ordoñez, 2014). The European money market combines both characteristics. Based on a peer-to-peer mechanism, unsecured lenders can monitor borrowers' credit risk. The anonymous CCP-based trading of secured loans is more opaque, in the sense that market participants have no precise information about the final borrowers and lenders and the CCP's (net) exposure to each of them. This implies that lenders can exercise market discipline on riskier (unsecured) loans by monitoring their borrowers, whereas safer (secured) loans are subject to asymmetric information. Repo lenders essentially mandate their protection to the CCP and its collateral policy. Our results suggest that this infrastructure is effective in disciplining *and* stabilizing wholesale funding.

The remainder of the paper is organized as follows. Section 1 discusses the main strands of theory on funding fragility and derives testable hypotheses. Section 2 presents the main institutional features of the unsecured and secured euro money markets, introduces the data, and analyzes various measures of money market activity. Sections 3 contains our joint empirical analysis of unsecured and secured borrowing and lending. Section 4 concludes.

1. Theoretical framework

In this section, we derive testable hypotheses from theory on money market dynamics and funding fragility. There are two main strands of the theoretical literature, which propose different explanations for funding fragility: liquidity hoarding and asymmetric information. We discuss each in turn.

1.1. Liquidity hoarding theories

The first strand of the literature focuses on liquidity hoarding, defined as a lender's propensity to reduce lending and hold more cash or central bank reserves. Liquidity hoarding may arise for precautionary or speculative motives. Precautionary liquidity hoarding may occur when lenders anticipate own liquidity needs. Theory suggests that this may happen if banks hold leveraged positions of illiquid, short-term assets (Acharya and Skeie, 2011) or suffer from tighter credit constraints and limited participation to wholesale funding markets (Ashcraft, McAndrews, and Skeie, 2011). It can also arise when agents expect general adverse situations such a larger aggregate liquidity demand (Allen, Carletti, and Gale, 2009), increases in Knightian uncertainty (Caballero and Krishnamurthy, 2008; Caballero and Simsek, 2013), larger credit risk (Heider, Hoerova, and Holthausen, 2015), or the fear of future illiquidity in case of asset liquidation (Bolton, Santos, and Scheinkman, 2011; Malherbe, 2014). The first hypothesis focuses on this precautionary motive.

Hypothesis 1 (H1): Banks hoard more liquidity when their risk increases.

A large share of the liquidity hoarding literature focuses on unsecured lending and lenders' tradeoff between reducing lending and liquidating assets. On the other hand, the recent literature on short-term debt highlights the importance of using assets as collateral to obtain short-term funding (e.g., Acharya, Gale, and Yorulmazer, 2011; Dang, Gorton, and Holmström, 2012; Holmström, 2015) and the inverse relationship between liquidity hoarding and the pledgeability of risky cash flows (Acharya, Shin, and Yorulmazer, 2011). Some recent papers study how collateralization affects liquidity hoarding. Gale and Yorulmazer (2013) compare two alternative economies: one with unsecured loans and one with secured (nonrecourse) ones. They show that the aggregate amount of liquidity and its allocation are efficient in the latter economy because only collateral assets are liquidated in the event of default. In Ahn et al. (2017) banks can obtain liquidity by selling or entering a repurchase agreement. If banks hold marketable securities with low value uncertainty, they hoard less liquidity. The second hypothesis is linked to these lower incentives to hoard liquidity when banks can lend against safe collateral. In a general equilibrium model, De Fiore, Hoerova, and Uhlig (2017) show that bank losing access to the unsecured market, but holding a sufficient amount of safe assets, can replace unsecured funding with secured funding. A similar substitution effect can occur in reaction to asset shocks (Ranaldo, Rupprecht, and Wrampelmeyer, 2016).

Hypothesis 2 (H2): Banks hoard less liquidity when they can lend against safe collateral.

The second motive to hoard liquidity is speculative. In theories with speculative liquidity hoarding, agents hoard more liquidity if they foresee higher expected returns coming from investment opportunities, such as the opportunity to buy assets at fire sale prices (Diamond and Rajan, 2011; Acharya, Shin, and Yorulmazer, 2011). The inefficient transfer of liquidity from banks with excess liquidity to banks with liquidity deficit can be exacerbated by the attempt to gain market power (Acharya, Gromb, and Yorulmazer, 2012). In Gale and Yorulmazer (2013), liquidity hoarding can arise from both precautionary and speculative motives. Speculative liquidity hoarding suggests a link between bank lending and banks' profits, which we include as third hypothesis.

Hypothesis 3 (H3): Banks hoard liquidity to exploit trading opportunities and increase profits.

1.2. Theories focusing on credit-risk and asymmetric information

The second strand of the theoretical literature on funding fragility and money market dynamics focuses on asymmetric information, meaning that borrowers know more about their credit quality than lenders. Within this strand, theories differ depending on whether lenders are uninformed or whether some lenders gain superior information about borrowers' credit risk. When all lenders are uninformed, asymmetric information can create credit rationing (Stiglitz and Weiss, 1981) with cascade effects and impairing the monetary policy transmission (Freixas and Jorge, 2008). Uninformed lenders apply the same credit conditions regardless of the specific credit quality of individual borrowers, leading to adverse selection as high-quality banks stop borrowing from the market (Heider, Hoerova, and Holthausen, 2015). These theories imply that high-quality borrowers leave the unsecured market in times of market stress and worsening credit risk. We summarize this prediction in hypothesis four.

Hypothesis 4 (H4): Borrowers with high credit worthiness borrow less in the unsecured market.

When some lenders are better informed due to monitoring, they discriminate between high- and low-quality borrowers (e.g., Diamond, 1984; Calomiris and Kahn, 1991; Von Thadden, 1995; Huang and Ratnovski, 2011; Rochet and Tirole, 1996). These theories suggest that informed lenders decrease lending and/or increase interest rates as a compensation for higher credit risk. They continue lending to banks with high credit quality. At the same time, uninformed lenders stop lending in the unsecured market completely because they fear a disadvantage compared with informed lenders in times of stress. These theories suggest that borrowers with low credit worthiness borrow less in the unsecured market and pay higher interest rates, which we state as hypothesis five.

Hypothesis 5 (H5): Borrowers with low credit worthiness borrow less in the unsecured market and pay higher interest rates.

Collateral provides protection to the lender and secured funding is less informationally sensitive (Dang, Gorton, and Holmström, 2012; Gorton and Ordoñez, 2014). Uninformed lenders, who are not willing to lend in the unsecured market, are still willing to lend in the secured market, in which informed lenders cannot profit from their superior information. Thus, borrowers who are perceived as low-quality by informed investors replace unsecured funding by secured funding as long as they have sufficient safe assets that can be used as collateral. In Hoerova and Monnet (2016), the quality of borrowers' investments is private information and lenders curb excessive risk-taking in the unsecured (secured) money market by peer monitoring (requiring collateral). When risky borrowers are rationed in the unsecured market, they choose to refinance in the secured market. This increase in secured lending of low-quality borrowers is summarized in hypothesis six.

Hypothesis 6 (H6): Banks with low credit worthiness borrow more in the secured market.

Below, we test all six hypotheses empirically.

2. The unsecured and secured interbank market in the euro area

2.1. Institutional background

The structure and institutional features of the euro money market provide an ideal setting to empirically test different hypotheses from money market theory. The unsecured money market considered in this study is the market for uncollateralized loans of reserve balances held by Eurosystem banks. On a daily basis, banks may access this market to meet reserve requirements set by the ECB and to satisfy their liquidity needs. Similar to the federal fund market in the United States, the unsecured money market is an over-the-counter market. Trades may be negotiated directly (for instance through the use of electronic platforms such as e-MID) or indirectly through a broker. Transactions in this market are based on relationships and on the periodic assessment of credit lines and credit merit among market participants. Trades are entered bilaterally and lenders are directly exposed to the borrowers' credit risk. Most interbank loans have an overnight maturity, with some transactions having longer duration (up to one year).

In addition to the unsecured market, banks in Europe may access the secured money market, which is also known as the repo market, to meet their short-term funding needs. This market has a unique infrastructure which has proven to be remarkably resilient during crisis periods. The key market features ensuring resilience are anonymous CCP-based trading, safe collateral, and the absence of an "unwind" mechanism (Mancini, Ranaldo, and Wrampelmeyer, 2016).[6] Trading anonymously via a CCP eliminates direct counterparty exposures between borrowers and lenders, so credit risk concerns are far less important than in the unsecured market. Safe collateral makes secured loans less informational sensitive. Moreover, haircuts are set by the CCP and in contrast to the United States, haricuts are not heterogenous across market participants (Gorton and Metrick, 2012; Copeland, Martin, and Walker, 2014).

2.2. Money market data and descriptive statistics

We use daily data of collateralized and uncollateralized borrowing and lending activity in Europe between June 2, 2008 and December 31, 2014, a period which spans 1,688 trading days. For the unsecured money market, we rely on data from TARGET2, the real-time gross settlement payment system owned and managed by the Eurosystem. Unsecured interbank loans with a maturity of one-day are extracted from TARGET2, relying on the methodology developed by Frutos et al. (2016).[7] This algorithm identifies interbank loans by matching cash flows between banks on different days, matching an initial payment from bank i to bank j at time t, with its re-payment from bank j to bank i at time $t + 1$. The algorithm requires the repayment to be equal the initial payment plus a plausible amount, representing the one-day interest rate.[8]

For the secured market, we use a repo data set consisting of all trades executed on Eurex Repo. Established in 2001, Eurex Repo GmbH is the leading electronic trading platform for euro General Collateral (GC) repos. For the analysis, we exclude all special repos, which tend to be driven by the demand for a particular collateral security rather than funding. Moreover, in line with our

[6] Prior to the ongoing U.S. triparty repo market reform, an unwinding of the repo trade occurred every morning; that is, collateral was returned to borrowers and lenders received back their cash. This gave borrowers the opportunity to substitute collateral and to adjust for price fluctuations. Until the repo agreement was rewound in the afternoon, the triparty clearing bank was lending to the repo borrower between this 8:00/8:30 a.m. unwind and the rewind after 3:30 p.m. Nowadays, much less intraday credit is extended by the clearing bank.

[7] The algorithm for identifying interbank loans with payment data is a refinement of the methodology originally developed by Furfine (2000).

[8] The algorithm does not distinguish different one-day term types (overnight, tomorrow-next, spot-next).

data for the unsecured market we focus on one-day repos. The Eurex Repo data set does not include any information about the identity of banks. However, it includes anonymous participant identifiers, which allows us to track the activity of a participant over time.

To merge the information from the secured and unsecured market, we use TARGET2 flows between individual banks and the CCP, Eurex Clearing, to match the participants in the unsecured and secured money market. This allows us to investigate how much and at what interest rate banks borrow and lend in the unsecured and secured market at any point in time. To reduce the impact of seasonal effects (see, e.g., Munyan, 2015; Abbassi, Fecht, and Tischer, 2017), we aggregate daily market data by Reserve Maintenance Period (RMP). The final sample consists of 79 banks over 80 RMPs.

Figure 1 shows the average daily trading volume, obtained by summing the daily average amounts traded by banks in our sample within each RMP. Looking at each market's aggregate activity, we observe that borrowing and lending amounts of the banks in our sample are very similar, with aggregate lending being slightly lower than aggregate borrowing in each market.[9] Looking at the two markets evolution, we observe opposite trends in the markets' relative size. Whereas the unsecured market is significantly larger in 2008, the secured market surpasses the unsecured market in terms of size in the second half of 2011. These patterns are in line with survey-based studies of aggregate market developments (e.g., European Central Bank, 2014), supporting the representativeness of our sample.

[Figure 1 about here]

For our regression analysis, we rely on RMP-average, bank-specific traded amounts and unsecured borrowing and lending shares, as illustrated in the previous section. Moreover, we define the average rates weighted by trade size for each bank, for each trading day, for borrowing and lending, and for both money markets. We then subtract from these rates the market rate, computed as the volume-weighted average rate for the entire market. Finally, for each bank we compute the average rate across all days included in a given RMP, to obtain RMP-average bank-specific interest rate spreads. Summary statistics for money market activity are shown in Table I.

[Table I about here]

[9] The amounts do not match exactly, because we consider unsecured (secured) borrowing and lending of the banks in our matched sample to and from all banks in the TARGET2 (Eurex repo) data.

2.3. Bank characteristics and market data

To be able to test the liquidity hoarding and credit risk hypotheses, we augment the money market data with credit rating time-series for each participant by combining information from Bloomberg and Bankscope. To measure credit risk for each bank, we translate the ratings of the rating agencies Standard & Poor's, Fitch, and Moody's into a numeric scale ranging from 1 (best) to 24 (worst). We then compute the average among these three ratings and compute the RMP average, to obtain one single bank-specific credit rating for each RMP. We adopt a similar procedure to compute a measure of each bank's country rating. If a bank rating is not available, we use the average rating from banks from that country. If a bank has no rating and is the only bank from that country we use the average rating of all banks in our sample for that day.

Summary statistics are shown in Table II. While there is variation in the riskiness of banks in our sample, the ratings indicate a rather high quality, with the average rating corresponding to A+ (for S&P and Fitch) and A1 for Moody's. We also collect information on bank characteristics, such as total assets, total equity, total funding, and leverage. These variables are only available on a yearly basis, so for a given RMP, we use the year-end values of the previous year.

In addition to bank characteristics, we collect data on market-wide developments as controls for our regression analysis. Given that some theories state that credit risk stems from aggregate market risk (e.g., Allen, Carletti, and Gale, 2009) rather than the credit risk specific to a given borrower, we include the composite indicator of systemic stress (CISS) of Hollo, Kremer, and Lo Duca (2012) as a general measure of risk in the European financial system. Lastly, as in Mancini, Ranaldo, and Wrampelmeyer (2016), we control for the liquidity in the financial system by computing aggregate excess reserves defined as Eurosystem's 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. We obtain these variables from the ECB statistical data warehouse.

[Table II about here]

3. Joint analysis of unsecured and secured borrowing and lending

In this section, we test the different hypotheses that we derived from theory in Section 1 by analyzing both lending and borrowing behavior of individual banks.

3.1. Precautionary liquidity hoarding

Liquidity hoarding theories pertain to the lending behavior of banks. Thus, to test liquidity hoarding theories we investigate money market lending. The first two hypotheses are related to the precautionary motive for liquidity hoarding. According to the theory, lenders' incentive to hoard liquidity increases when their own riskiness increases. We test this by regressing banks' lending volume on their own credit risk as measured by their credit rating. Given potential endogeneity, i.e., money market activity might affect credit ratings, we use credit ratings from the previous RMP[10]:

$$LendingVolume_{i,t}^{m} = \beta_0 + \beta_1 \cdot CreditRisk_{i,t-1} + \beta_2 \cdot Controls_{i,t-1} + \gamma_t + \lambda_i + \varepsilon_{i,t} \qquad (1)$$

where $m \in \{total, UMM, SMM\}$ where UMM and SMM refer to unsecured and secured money markets. $Controls_{i,t-1}$ denotes a set of bank-specific variables and macro variables as discussed in Section 2.2. We also include time fixed-effects γ_t as well as bank fixed-effects λ_i to control for market-wide developments, such as new regulation, and bank heterogeneity that are not captured by the other variables.

To be able to test H1 and H2 it is crucial to run regression (1) separately for secured and unsecured lending. Table III shows the regression results. On the one hand, unsecured lending volume declines with credit risk as predicted by classic liquidity hoarding theories and in line with previous empirical findings on precuationary liquidity hoarding (Acharya and Merrouche, 2013; Ashcraft, McAndrews, and Skeie, 2011). On the other hand, secured volume increases with credit risk. This finding highlights that it is crucial to investigate secured and unsecured lending simultaneously when testing liquidity hoarding theories. When investigating the total lending volume, we do not find evidence to support H1. Lenders reduce unsecured lending but instead of hoarding liquidity they lend more in the secured market.

In contrast, our results provide support for H2: Lenders hoard less liquidity when they can lend against safe collateral. Actually, Table III shows that the reduction in unsecured lending seems to be offset by an increase in secured lending and that there is no liquidity hoarding. This suggests that lenders with higher credit risk continue to lend and there is no precautionary liquidity hoarding

[10] Our results are robust to using a forward looking measure of credit risk; the results are shown in the Internet Appendix.

in the classic sense. However, lenders are precautionary in the sense that they prefer to lend against safe collateral to reduce their risk exposure, reinforcing the idea that collateral quality is crucial for repo markets (Mancini, Ranaldo, and Wrampelmeyer, 2016; Boissel et al., 2017). This is also in line with empirical evidence that lenders are more concerned about risky or illiquid collateral rather than unwilling to lend to specific counterparties (Krishnamurthy, Nagel, and Orlov, 2014).

[Table III about here]

3.2. Speculative liquidity hoarding

In addition to precautionary motives, banks may have speculative reasons for liquidity hoarding. Such speculative liquidity hoarding is the subject of H3, which states that lenders hoard liquidity for speculative reasons to exploit profitable trading opportunities and earn higher profits. To test this hypothesis, we relate banks profits to their lending behavior. Balance sheet information about profitability is only available on an annual basis, so we run the following regression with annual data:

$$\Delta ROA_{i,y} = \beta_0 + \beta_1 \cdot \Delta LendingVolume_{i,y} + \beta_2 \cdot Controls_{i,y-1} + \gamma_y + \lambda_i + \varepsilon_{i,y} \quad (2)$$

The dependent variable is the change in ROA between year y and $y-1$. To test whether a reduction in lending increases profits, we determine banks' average daily lending volume for each year and use the change from year y to $y-1$, $\Delta LendingVolume_{i,y}$, as our main explanatory variable. Results for different specifications with and without control variables, $Controls_{i,y-1}$, and fixed effects, $\gamma_y$and λ_i are shown in Table IV. We also repeat the analysis interacting the change in lending with a crisis dummy which equals one during the height of the Eurozone crisis in 2010 and 2011. Lastly, we replace the change in lending volume by a dummy which is one when lender i increased volume in year y.

[Table IV about here]

None of the specifications indicates a significant negative relation between changes in lending volume and ROA. This is true when investigating total lending volume as well as unsecured volume only. The signs of the point estimates are negative, i.e., in line with speculative liquidity hoarding when solely looking at unsecured lending. However, they are positive and do not support speculative liquidity hoarding when analyzing total lending volume. Overall, our results do not support H3.

3.3. Credit risk and asymmetric information

We analyze unsecured and secured *borrowing* to test H4 to H6, which focus on theories that explain funding fragility by credit risk and asymmetric information. We rely on a similar regression design as Equation 1 with borrowing volume instead of lending volume:

$$BorrowingVolume_{i,t}^{m} = \beta_0 + \beta_1 \cdot CreditRisk_{i,t-1} + \beta_2 \cdot Controls_{i,t-1} + \gamma_t + \lambda_i + \varepsilon_{i,t}. \tag{3}$$

H4 and H5 make opposite predictions about the effect of credit risk on unsecured borrowing. According to adverse selection theories (H4), credit risk is positively related to unsecured borrowing volume. In times of high risk, lenders do not differentiate between borrowers, such that there is adverse selection and high quality borrowers borrow less in the unsecured market. In contrast, when some lenders are informed by monitoring borrowers, higher credit risk should lead to less unsecured borrowing (H5).

Table V shows the regression results. The results do not support H4 as credit risk is negatively related to unsecured borrowing. Rather than adverse selection theories assuming uniformly uniformed lenders, our results support theories in which some lenders are informed and monitor borrowers providing further empirical support to peer monitoring in unsecured money markets in the United States (Ashcraft and Duffie, 2007; Furfine, 2001) and in the European non-interbank wholesale funding market (Perignon, Thesmar, and Vuillemey, 2018). As predicted by H5, banks with a worse credit rating tend to borrow less in the unsecured market. This in line with the previous empirical literature on the FED funds market in the United States (Afonso, Kovner, and Schoar, 2011b).

[Table V about here]

To test whether lenders also increase interest rates to lower quality borrowers, we compute the spread over average interest rates in the unsecured market for each borrower and regress it on credit risk:

$$Spread_{i,t}^{m} = \beta_0 + \beta_1 \cdot CreditRisk_{i,t-1} + \beta_2 \cdot Controls_{i,t-1} + \gamma_t + \lambda_i + \varepsilon_{i,t}. \tag{4}$$

The regression results in Table VI show that the spreads of banks increase with credit risk, but the magnitude is economically small and mostly statistically insignificant. A simple supply and demand framework (Garcia-de-Andoain et al., 2016) offers an economic interpretation of these patterns. In reaction to a negative liquidity shock, both a demand and supply reduction decrease credit volumes whereas a significant decrease of interest rates is more consistent with a demand reduction, only. Our finding that credit risk in the euro money market mainly affects quantities is also in line with theories in which some lenders are informed, but rates remain stable and inelastic (Huang and Ratnovski, 2011) even in distressed markets (Furfine, 2002).

[Table VI about here]

The last hypothesis (H6) is based on recent theories about differences between unsecured and secured funding. The empirical prediction is that when there is credit rationing to lower-quality banks in the unsecured market, these banks borrow more in the secured market, which is not information sensitive. This substitution is supported by the regression results shown in V. Low quality banks borrow less in the unsecured market, but at the same time, their borrowing in the secured market increases by a similar amount. This suggests that banks are able to compensate the reduction in unsecured borrowing by borrowing more in the secured market. The regression estimates in Tables V are also significant in economic terms. On average over our sample period, a bank rated as non-investment grade speculative (i.e., a S&P and Fitch's BB, or a Moody's Ba2) borrows approximately EUR 154 millions less of unsecured funding on a daily basis compared with a top-rated bank (AAA). In contrast, the lower rated bank would be able to raise a similar amount of secured funding.

To summarize, our results show that credit risk negatively affects the unsecured money market. In line with theories in which some lenders are informed, banks with worse credit ratings borrow less. However, these banks are able to replace their unsecured funding in the secured money market, highlighting the importance of the information insensitivity of secured funding from a financial stability perspective.

3.4. Vulnerable banks

Which banks are able to substitute a loss in unsecured funding by more secured funding? Banks that are perceived as risky and lose unsecured funding, can only borrow in the secured market if they have sufficient safe collateral. This implies that the ability to substitute unsecured with secured borrowing depends on borrowers' riskiness. In this subsection, we analyze whether the ex-ante risk profile of a bank, as measured by leverage before the outbreak of the Lehman collapse, can predict how borrowers rely upon the unsecured and secured money market during the crisis.

We group banks into low leverage (below median) and high leverage (above median) banks and run the benchmark volume regression separately for these groups. Our results in Table VII show that higher initial leverage is associated with a larger decrease of unsecured borrowing, consistent with the credit monitoring theory. Second, it is more difficult to substitute unsecured borrowing with secured loans for banks with higher leverage.

[Table VII about here]

3.5. Robustness analysis

Our results are robust to alternative econometric specifications and an event study controlling for central bank liquidity also supports our findings. We provide the corresponding results in the following subsections.

3.5.1 Alternative econometric specification

Instead of analyzing UMM and SMM activity separately, we can directly investigate the relative reliance of banks on unsecured and secured borrowing and lending:

$$ShareUMM_{i,t}^{d} = \beta_0 + \beta_1 \cdot CreditRisk_{i,t-1} + \beta_2 \cdot Controls_{i,t-1} + \gamma_t + \lambda_i + \varepsilon_{i,t}, \tag{5}$$

where $d \in \{borrowing, lending\}$ and $ShareUMM_{i,t}^{d} = \frac{Volume_{i,t}^{UMM,d}}{Volume_{i,t}^{UMM,d} + Volume_{i,t}^{SMM,d}}$.

Table VIII shows the regression results. Consistent with the findings above, lenders' share of unsecured borrowing decreases in line with H2. Banks with higher credit risk have a lower share of unsecured borrowing, providing further support for H5 and H6. Our results are also robust when using a dynamic panel model to account for persistence in money market variables or when using alternative measures of credit risk. We provide detailed results in the Internet Appendix.

[Table VIII about here]

3.5.2 Event study

In this section, we provide evidence that individual banks' borrowing from the central bank's primary credit facility does not affect our results. To that end, we exploit the known timing of the ECB's liquidity operations and analyze banks' borrowing and lending behavior around rating downgrades when banks' liquidity obtained through regular ECB operations is fixed.

The ECB conducts open market operations mainly through repos in its main refinancing operations (MRO). Since October 2008, these operations have a fixed-rate, full-allotment (FRFA) format, meaning banks can obtain as much liquidity as they want at the prevailing MRO rate as long as they have sufficient collateral. As explained in Garcia-de-Andoain et al. (2016), these liquidity operations take place on a weekly basis, implying that banks can change the level of liquidity borrowed from the central bank only on certain days.[11] More precisely, MROs are conducted on Tuesdays and banks receive the amount borrowed on Wednesday morning. Thus, banks' liquidity obtained from the central bank is fixed between Wednesday and the next MRO on the following Tuesday.

This operational framework allows us to analyze the effect of rating downgrades on money market borrowing controlling for individual banks' level of central bank borrowing. More precisely, we conduct an event study for rating downgrades on days on which central bank liquidity is fixed, i.e., Wednesday, Thursday, and Friday. We use an event window of two days (day t and $t+1$) to account for rating change announcements after market close. We compute banks' average abnormal borrowing (AAB) and average abnormal lending (AAL) for the total money market, for the unsecured money market, for the secured money market, and for the share of unsecured money market volume. These quantities are defined as the difference between event window averages and the normal value, which we compute as the average borrowing and lending volumes and the average share of unsecured borrowing and lending over an estimation window of 20 days prior to the downgrade.

Despite the limited number of observations, the results are in Table IX are in line with our previous findings. Borrowers tend to reduce unsecured borrowing and increase secured borrowing in the two days following a downgrade, whereas total borrowing volume does not change significantly. On the lending side, we again do not find evidence of liquidity hoarding.

[Table IX about here]

[11]In addition, banks can obtain liquidity on a daily basis through the marginal lending facility, which is similar to the Feds discount window. In the FRFA regime, the use of the marginal lending facility was extremely limited (Garcia-de-Andoain et al., 2016). Thus, we focus on regular liquidity operations, which provide the vast majority of ECB liquidity.

4. Conclusion

This paper investigates why wholesale funding is fragile by providing the first joint analysis of the secured and unsecured money markets of the euro area at a bank level. Our analysis uncovers two important substitution mechanisms. On the lending side, riskier banks reduce their uncollateralized lending, as predicted by the classic models of liquidity hoarding for precautionary motives. However, this reduction is offset by more collateralized lending. Thus, in line with the most recent theoretical literature on secured lending, banks hoard less liquidity when they can access the secured money market. Overall, our results suggest that riskier banks are precautionary in the sense that they prefer to lend in the secured market against high quality collateral rather than in the sense that they hoard cash.

On the borrowing side, banks bearing higher credit risk are subject to funding strains (lower borrowing volume) in the unsecured market. However, these banks are able to replace unsecured funding with secured borrowing. Given that lenders know their counterparty in the unsecured market but not in the secured market, our findings are consistent with theories in which some lenders monitor and discriminate borrowers with lower credit worthiness. At the same time, borrowers holding assets that qualify as collateral for secured lending can satisfy their funding needs in the secured market regardless of their perceived credit worthiness.

Our study delivers key insights for academics, market participants, and policy makers. First, it highlights the importance of a joint analysis of the unsecured and secured components of money markets. On the lending side, a separate inspection would overemphasize the precautionary motives of liquidity hoarding. It would also overlook the important role of secured lending to facilitate an efficient allocation of liquidity from banks with liquidity surplus to those with liquidity deficits. On the borrowing side, a disaggregate analysis would miss how critical collateral assets are to be able to substitute unsecured with secured funding. Second, our findings suggest that secured funding is crucial for the reduction of financial fragility. The secured market facilitates the substitution of unsecured funding with secured liquidity, especially for banks bearing higher credit risk. To do this, banks need to hold assets eligible for secured funding thereby providing liquidity buffers, which is exactly in the spirit of the new liquidity requirements such as the Liquidity Coverage and Net Stable Funding Ratios. Third, our analysis provides insights for the ongoing reform of wholesale funding. One of the main issues is the degree of transparency that should be implemented. Our results suggest that transparency helps lenders monitor and enforce market discipline in the riskier part of wholesale funding, i.e., the unsecured segment. On the other hand, opaqueness in the form of trading anonymity, can be beneficial in secured markets with safe collateral and reduce fragility.

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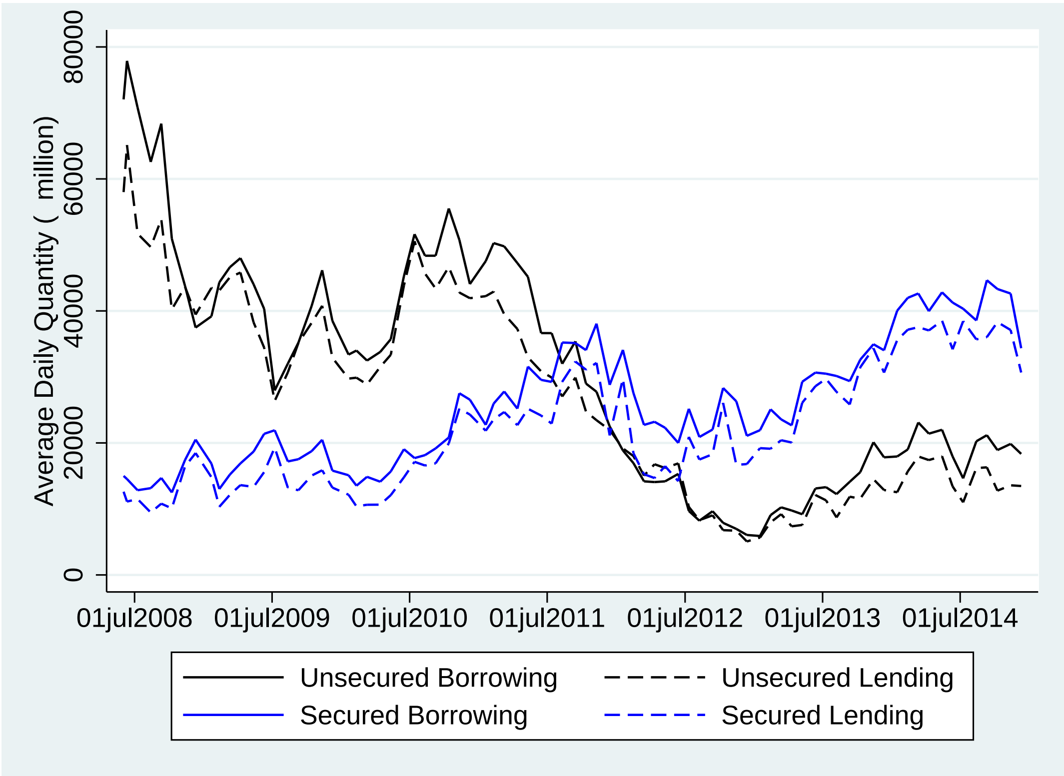

Figure 1. Average daily volume of money market transactions. The figure shows the daily averages within each reserve maintenance period from June 2008 to December 2014 of aggregate trading in the unsecured and secured markets (in millions of Euros). The black (blue) lines refer to the unsecured (secured) market and continuous (dashed) lines refer to borrowing (lending), respectively.

Table I
Descriptive statistics for money market activity

This table shows descriptive statistics of money market variables. We present the number of observations (obs), median, mean, standard deviation (std. dev.), 25% and 75% percentiles (25% and 75%). Interest rates are computed relative to the market rate and as daily volume-weighted average rates. Quantities refer to daily amount of transactions in EUR millions. Unsecured and secured borrowing (lending) are labeled "Unsec. Borrow" and "Sec. Borrow" ("Unsec. Lend" and "Sec. Lend"). The sample consists of 6,320 observations, including 79 banks during 80 reserve maintenance periods (RMPs) from June 2008 to December 2014. The variables include one observation per bank per RMP. The number of observations varies across variables because banks do not trade on all markets in each RMP.

Variables	Obs.	25%	Median	Mean	75%	Std. Dev.
Volume (mln)						
Total Borrowing	4,577	55	373	987	1,342	1,474
Total Lending	4,845	39	210	805	834	1,853
Unsec. Borrow	3,848	44	263	641	845	989
Unsec. Lend	4,046	12	92	533	433	1,440
Sec. Borrow	3,023	40	202	679	829	1,116
Sec. Lend	2,963	33	150	589	534	1,655
Share unsecured (% of total volume)						
Borrow	4,577	13	74	59	100	41
Lend	4,845	4	81	59	100	44
Spreads (basis points)						
Unsec. Borrow	3,848	-3.26	-0.38	0.19	3.00	10.86
Unsec. Lend	4,046	-2.74	0.51	1.46	4.38	12.57
Sec. Borrow	3,023	-1.96	-0.49	-0.42	0.96	4.91
Sec. Lend	2,963	-1.61	-0.06	0.52	2.02	11.38

Table II
Balance Sheet Information of Market Participants

The table shows balance sheet information in terms of credit risk, leverage ratio, total equity, assets and funding. Leverage ratio is expressed in % and remaining variables in billions of Euros. Credit risk is measured as the worst bank rating of a homogenized scale ranging from 1 (best) to 25 (worst) across Standard & Poor's, Fitch, and Moody's. The descriptive statistics are the number of observations (obs), median, mean, standard deviation (std. dev.), 25% and 75% percentiles (25% and 75%). The sample period spans from June 2007 to December 2014 including 80 reserve maintenance periods (RMPs) and 79 banks. Balance sheet characteristics include one observation per bank per year. The last row shows Eurosystem's Excess Reserves (EUR billions), computed as banks' balances 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.

Balance sheet variables	Obs.	25%	Median	Mean	75%	Std. Dev.
Borrower Characteristics						
Credit Risk	6'320	4	6	5.84	7	1.9
Leverage Ratio	538	3.11	4.22	5.27	5.91	5.03
Total Equity	542	1	7	20	31	27
Total Assets	539	13	150	440	670	580
Total Funding	539	13	140	380	590	500
Market characteristics						
Excess reserves (bn)	80	76	160	229	263	226
CISS	80	0.105	0.296	0.305	0.416	0.209

Table III
Lending Volume

This table shows the panel regression results for money market lending volumes. The depended variables are the average daily bank's volume of total, unsecured, and secured lending across the reserve maintenance periods. The dependent variables are regressed on a measure of credit risk based on the banks' credit ratings. Column (1) reports the regression results without including any controls or fixed-effects. Columns (2) to (4) include different combinations of bank-specific as well as market-wide control variables and fixed effects. The bottom of the table shows the number of observations, the number of banks, and the regression R-squares. Robust standard errors (clustered at the bank level) are reported in parenthesis. Significance at 1%, 5%, and 10% is denoted by $***$, $**$, and $*$, respectively.

	Total				UMM				SMM			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$CreditRisk_{i,t-1}$	30.16	112.3	168.8	130.3	-147.2	-208.5***	-234.2**	-273.5**	177.4	320.9	403.0	403.8
	(194.9)	(280.5)	(361.3)	(365.1)	(98.67)	(77.34)	(93.72)	(108.2)	(174.9)	(275.2)	(352.1)	(353.2)
$Size_{i,t-1}$			-445.9	-468.9			-226.1	-285.5			-219.8	-183.4
			(315.2)	(352.0)			(222.7)	(225.0)			(229.1)	(256.1)
$Leverage_{i,t-1}$			18.16	14.44			8.783	7.315			9.379	7.121
			(12.02)	(11.03)			(6.845)	(5.769)			(9.301)	(8.771)
$Capital_{i,t-1}$			23.61	9.418			15.61	-9.670			8.004	19.09
			(20.16)	(19.78)			(12.70)	(13.14)			(17.40)	(15.33)
$ImpairedLoans_{i,t-1}$			8.858	8.648			3.184	2.613			5.675	6.036
			(6.576)	(6.081)			(3.344)	(3.009)			(5.701)	(5.423)
$Profitability_{i,t-1}$			-74.30	-86.47			-23.33	-31.41			-50.97	-55.06
			(94.20)	(78.60)			(33.72)	(23.59)			(91.59)	(72.74)
$ExcessReserves_t$				-942.2**				-451.3**				-490.9
				(357.4)				(183.0)				(303.9)
$MarketwideRisk_t$				540.3**				345.9**				194.4
				(217.5)				(163.3)				(139.8)
Constant	455.0	465.0	8,442	8,494	1,110*	1,753***	6,248	7,279	-655.4	-1,288	2,194	1,215
	(1,003)	(1,362)	(5,804)	(6,180)	(609.9)	(494.7)	(4,581)	(4,634)	(847.5)	(1,282)	(3,600)	(3,700)
Bank FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No
Observations	6,241	6,241	3,749	3,749	6,241	6,241	3,749	3,749	6,241	6,241	3,749	3,749
Number of banks	79	79	61	61	79	79	61	61	79	79	61	61
R-squared	0.003	0.075	0.102	0.080	0.019	0.098	0.128	0.107	0.027	0.056	0.092	0.087

Table IV
Lending and Profitability

In this table, we show how profitability is related to lending behavior. The dependent variable in the regression is Changes in ROA between the end of year $y1$ and the end of year y. $\Delta Volume_{i,y}^{total,lend}$ and $\Delta Volume_{i,y}^{UMM,lend}$ are the changes in total lending and in UMM lending during the same period, respectively. In columns (1) to (4) we investigate total lending; columns (5) to (8) show the results for UMM lending only. Columns (1) and (5) show the benchmark specification with bank and time fixed effects. In column (2) and (6) we add control variables measured at the end of year $y-1$. Controls include size, ROA, impaired loans over total loans, leverage, and the credit rating. In columns (3) and (7) we interact changes in lending with a $Crisis$ dummy that equals one in 2011 and 2012. Columns (4) and (8) show results when replacing the change in lending volume in the benchmark specification with a dummy variable that equals 1 when banks increased lending between $y-1$ and y. The last rows of the table show the number of observations and the regression R-squares. Robust standard errors (clustered at the bank level) are reported in parenthesis. Significance at 1%, 5%, and 10% is denoted by $***$, $**$, and $*$, respectively.

Dependent Variable: $\Delta ROA = ROA_t - ROA_{y-1}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta Volume_{i,y}^{total,lend}$	0.0449	0.00384	0.0293					
	(0.0387)	(0.0246)	(0.0310)					
$\Delta Volume_{i,y}^{UMM,lend}$					-0.0273	-0.0111	-0.0198	
					(0.0464)	(0.0259)	(0.0552)	
$\Delta Volume_{i,y}^{total,lend} \cdot Crisis$			-0.0769					
			(0.0573)					
$\Delta Volume_{i,y}^{UMM,lend} \cdot Crisis$							0.0153	
							(0.0624)	
$TotalLendingIncrease$				0.118				
				(0.0855)				
$UMMLendingIncrease$								-0.0628
								(0.0854)
Constant	-0.564***	0.692	0.739	-0.496***	-0.633***	1.335	1.325	-0.688***
	(0.0980)	(1.050)	(1.055)	(0.114)	(0.0135)	(1.380)	(1.392)	(0.0854)
Control variables	No	Yes	Yes	No	No	Yes	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	396	290	290	396	336	245	245	336
R-squared	0.448	0.803	0.804	0.450	0.311	0.618	0.618	0.312

Table V
Borrowing Volume

This table shows the panel regression results for money market borrowing volumes. The depended variables are the average daily bank's volume of total, unsecured, and secured borrowing across the reserve maintenance periods. The dependent variables are regressed on a measure of credit risk based on the banks' credit ratings. Column (1) reports the regression results without including any controls or fixed-effects. Columns (2) to (4) include different combinations of bank-specific as well as market-wide control variables and fixed effects. The bottom of the table shows the number of observations, the number of banks, and the regression R-squares. Robust standard errors (clustered at the bank level) are reported in parenthesis. Significance at 1%, 5%, and 10% is denoted by $***$, $**$, and $*$, respectively.

	Total				UMM				SMM			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$CreditRisk_{i,t-1}$	-134.7	0.675	52.09	24.40	-174.1***	-159.4**	-167.7*	-214.6**	39.47	160.0**	219.8***	239.0***
	(84.39)	(98.24)	(128.2)	(127.8)	(62.08)	(76.39)	(88.95)	(92.79)	(45.94)	(63.02)	(65.56)	(65.37)
$Size_{i,t-1}$			7.282	58.21			175.0	130.1			-167.7	-71.91
			(212.3)	(225.6)			(122.0)	(119.2)			(185.1)	(193.4)
$Leverage_{i,t-1}$			2.059	-1.148			3.521	1.794			-1.463	-2.941
			(2.614)	(2.781)			(2.175)	(2.153)			(1.874)	(1.921)
$Capital_{i,t-1}$			-0.0693	7.689			1.735	-21.29			-1.805	28.98*
			(20.39)	(19.79)			(15.82)	(13.43)			(13.25)	(17.11)
$ImpairedLoans_{i,t-1}$			-2.804	-2.252			0.229	-0.118			-3.033**	-2.134*
			(2.618)	(2.080)			(1.836)	(1.714)			(1.402)	(1.080)
$Profitability_{i,t-1}$			-67.84	-70.70			-49.61	-50.34			-18.23	-20.36
			(49.63)	(54.35)			(35.54)	(34.88)			(28.51)	(32.34)
$ExcessReserves_t$				-992.4***				-681.4***				-311.0***
				(209.4)				(138.3)				(100.7)
$MarketwideRisk_t$				297.6				189.0				108.6
				(233.8)				(127.6)				(188.8)
Constant	1,419***	1,167**	1,319	-23.08	1,300***	1,695***	-1,380	-557.0	118.6	-528.5*	2,699	533.9
	(487.3)	(492.2)	(4,113)	(4,397)	(363.7)	(427.4)	(2,351)	(2,300)	(247.2)	(299.5)	(3,556)	(3,770)
Bank FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No
Observations	6,241	6,241	3,749	3,749	6,241	6,241	3,749	3,749	6,241	6,241	3,749	3,749
Number of banks	79	79	61	61	79	79	61	61	79	79	61	61
R-squared	0.012	0.057	0.089	0.061	0.054	0.153	0.210	0.165	0.003	0.075	0.102	0.080

Table VI
Interest Rate Spreads for Unsecured Borrowing

This table shows the panel regression results for money market borrowing spreads. The depended variables is the volume-weighted spread for unsecured borrowing across the reserve maintenance periods (RMPs) for bank i in RMP t. The spread at time t is computed as the rate of bank i minus the volume-weighted market average rate at t. The dependent variables are regressed on a measure of credit risk based on banks' credit ratings. Column (1) reports the regression results without including any controls or fixed-effects. Columns (2) to (4) include different combinations of bank-specific as well as market-wide control variables and fixed effects. The bottom of the table shows the number of observations, the number of banks, and the regression R-squares. Robust standard errors (clustered at the bank level) are reported in parenthesis. Significance at 1%, 5%, and 10% is denoted by $***$, $**$, and $*$, respectively.

	$Spread_{i,t}^{UMM,borr}$			
	(1)	(2)	(3)	(4)
$CreditRisk_{i,t-1}$	0.0118***	0.00778	0.00921	0.00876
	(0.00371)	(0.00561)	(0.00597)	(0.00555)
$Size_{i,t-1}$			0.00453	0.00451
			(0.0271)	(0.0266)
$Leverage_{i,t-1}$			-0.000313	-0.000375
			(0.000408)	(0.000372)
$Capital_{i,t-1}$			-0.00555**	-0.00501**
			(0.00272)	(0.00245)
$ImpairedLoans_{i,t-1}$			-0.000115	-0.000107
			(0.000161)	(0.000151)
$Profitability_{i,t-1}$			0.0137**	0.0137**
			(0.00591)	(0.00617)
$ExcessReserves_t$				-0.0367
				(0.0242)
$MarketwideRisk_t$				-0.0693**
				(0.0328)
Constant	-0.0685***	-0.0416	-0.0660	-0.0501
	(0.0206)	(0.0321)	(0.529)	(0.507)
Bank FE	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	No
Observations	3,802	3,802	2,703	2,703
Number of banks	70	70	53	53
R-squared	0.024	0.108	0.091	0.029

Table VII
Borrowing of low leverage vs. high leverage banks

This table shows the panel regression results for money market volumes for low leverage (below median) and high leverage (above median) banks. The dependent variables are regressed on a measure of credit risk based on the banks' credit ratings as well as bank-specific control variables. The bottom of the table shows the number of observations, the number of banks, and the regression R-squares. Robust standard errors (clustered at the bank level) are reported in parenthesis. Significance at 1%, 5%, and 10% is denoted by $***$, $**$, and $*$, respectively.

	Low leverage		High leverage	
	$Volume^{borr}_{i,t}$		$Volume^{borr}_{i,t}$	
	UMM	SMM	UMM	SMM
$CreditRisk_{i,t-1}$	-131.1*	194.4**	-194.3***	120.6***
	(66.88)	(74.43)	(68.15)	(39.13)
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	3,062	3,062	3,007	3,007
Number of banks	60	60	55	55
R-squared	0.121	0.148	0.222	0.059

Table VIII
Share of Unsecured Volume

This table shows the panel regression results for the share of money market volumes. In columns (1) to (4), the depended variable is the share of unsecured borrowing. In columns (5) to (8), the depended variable is the share of unsecured lending. The dependent variables are regressed on a measure of credit risk based on the banks' credit ratings. Columns (1) and (5) report the regression results without including any controls or fixed-effects. Columns (2) to (4) and (6) to (8) include different combinations of bank-specific as well as market-wide control variables and fixed effects. The bottom of the table shows the number of observations, the number of banks, and the regression R-squares. Robust standard errors (clustered at the bank level) are reported in parenthesis. Significance at 1%, 5%, and 10% is denoted by $***$, $**$, and $*$, respectively.

	$Share_{i,t}^{UMM,borr}$				$Share_{i,t}^{UMM,lent}$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$CreditRisk_{i,t-1}$	-0.0531**	-0.0534***	-0.0986***	-0.119***	-0.0225	-0.0456*	-0.0793***	-0.0986***
	(0.0214)	(0.0198)	(0.0233)	(0.0242)	(0.0367)	(0.0249)	(0.0239)	(0.0203)
$Size_{i,t-1}$			0.00311	-0.0436			-0.0620	-0.109
			(0.0854)	(0.0814)			(0.0712)	(0.0712)
$Leverage_{i,t-1}$			0.00178	0.00163			0.00389*	0.00501**
			(0.00174)	(0.00173)			(0.00228)	(0.00227)
$Capital_{i,t-1}$			0.0168	-0.00440			0.0135	-0.00415
			(0.0104)	(0.00815)			(0.0112)	(0.00886)
$ImpairedLoans_{i,t-1}$			0.000658	0.000130			-2.07e-05	-0.000281
			(0.000823)	(0.000963)			(0.000882)	(0.000828)
$Profitability_{i,t-1}$			0.0244	0.0102			0.0125	0.0193
			(0.0319)	(0.0310)			(0.0202)	(0.0180)
$ExcessReserves_t$				-0.0993**				-0.0432
				(0.0489)				(0.0627)
$MarketwideRisk_t$				0.0920				0.0463
				(0.0638)				(0.0775)
Constant	0.872***	1.041***	0.925	2.055	0.700***	1.049***	2.155	3.149**
	(0.118)	(0.0849)	(1.696)	(1.601)	(0.201)	(0.118)	(1.441)	(1.423)
Bank FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	No	Yes	Yes	No
Observations	4,528	4,528	3,077	3,077	4,528	4,528	3,077	3,077
Number of banks	79	79	61	61	79	79	61	61
R-squared	0.022	0.242	0.229	0.176	0.022	0.242	0.229	0.176

Table IX
Event study

This table shows the results from the event study. To identify the event dates, we focus on rating downgrades on days during which central bank liquidity is fixed, i.e., Wednesday, Thursday, and Friday. We define the event window as the day of the downgrade and the day following the downgrade. We compute average abnormal values (average abnormal borrowing, AAB, and average abnormal lending (AAL) for each variable as the difference between event window averages and the normal value. We compute normal values as the average borrowing and lending volumes and the average share of unsecured borrowing and lending over an estimation window of 20 days prior to the downgrade. Our samples include banks that borrowed/lent in both markets during the estimation and event window.

	Borrowing			
	$Volume^{total}$	$Volume^{UMM}$	$Volume^{SMM}$	$Share^{UMM}$
AAB	72.5	−373.1	445.6	−0.088**
Std. error	340.4	236.2	245.3	0.038
No. of events	31	31	31	31
	Lending			
	$Volume^{total}$	$Volume^{UMM}$	$Volume^{SMM}$	$Share^{UMM}$
AAL	1064.8*	588.7	476.1	-0.013
Std. error	600.5	483.2	362.0	0.020
No. of events	17	17	17	17

Internet Appendix for "Unsecured and Secured Funding"

April 10, 2018

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

IA.1. Additional results

IA.1.1. Aggregate market developments

In this subsection we provide further details on aggregate developments. Figure IA.1 shows the volume-weighted average rates in the unsecured and secured markets. Interestingly, we observe that in 55 out of 80 RMPs, the average market rate in the secured market is higher than the average market rate in the unsecured market. This suggests that banks that were able to borrow in the unsecured market could do so at low rates. The average unsecured rate is significantly higher than the secured rate in the second half of 2012, when secured rates decreased with the ECB deposit rate, whereas unsecured rates remained more positive.

Figure IA.2 presents the average number of daily transactions in the two markets, confirming the decrease of activity in the unsecured market shown in Figure 1. The number of daily transactions in the unsecured market decreases from an initial 500–600 at the beginning of our sample to reach a minimum of about 100 daily transactions in the second quarter of 2012. The number of transaction in the secured market was low in the beginning of the sample, but reached 150 in 2014.

Finally, Figure IA.3 displays the daily average unsecured market shares for both lending and borrowing activity, obtained by first computing, for each bank, the ratio of unsecured borrowing (lending) over total borrowing (lending) during a given RMP, and then by averaging this measure across the 79 banks in the sample. In line with the aggregate volume figures, both lending and borrowing shift over time to the secured segment.

IA.1.2. Lending Spreads

Table IA.1 shows the regression results for interest rate spreads earned by lenders. Overall, the effects of bank ratings on spreads are smaller than the ones for quantities, suggesting that credit risk in the euro money market mainly affects quantities. Interest rates for all forms of lending tend to increase with higher credit rating, but the magnitude is economically small.

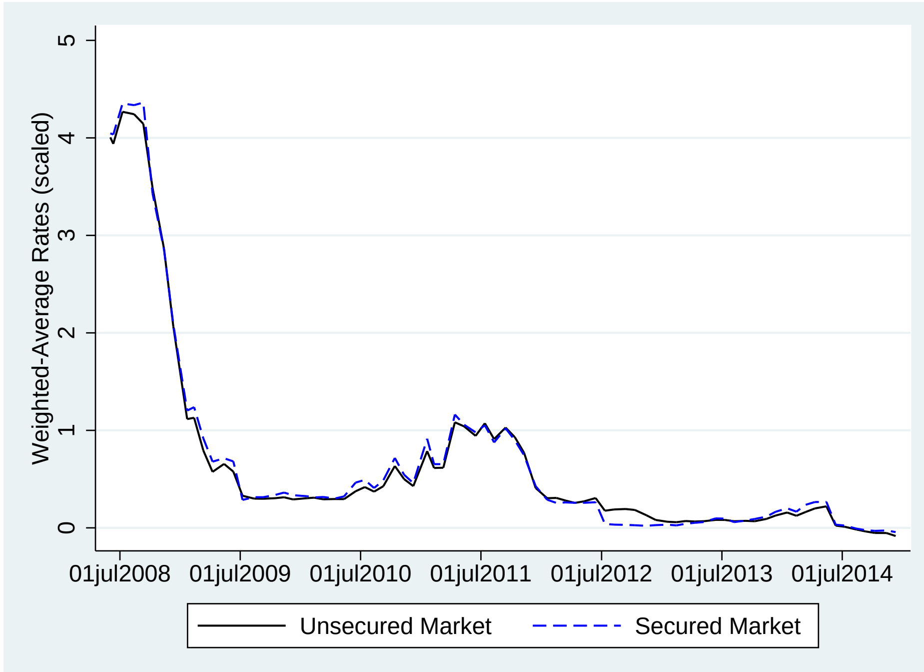

Figure IA.1. Money market interest rates. The continuous and dashed lines show the volume weighted average rates for each reserve maintenance period from June 2008 to December 2014 in the unsecured and secured money markets.

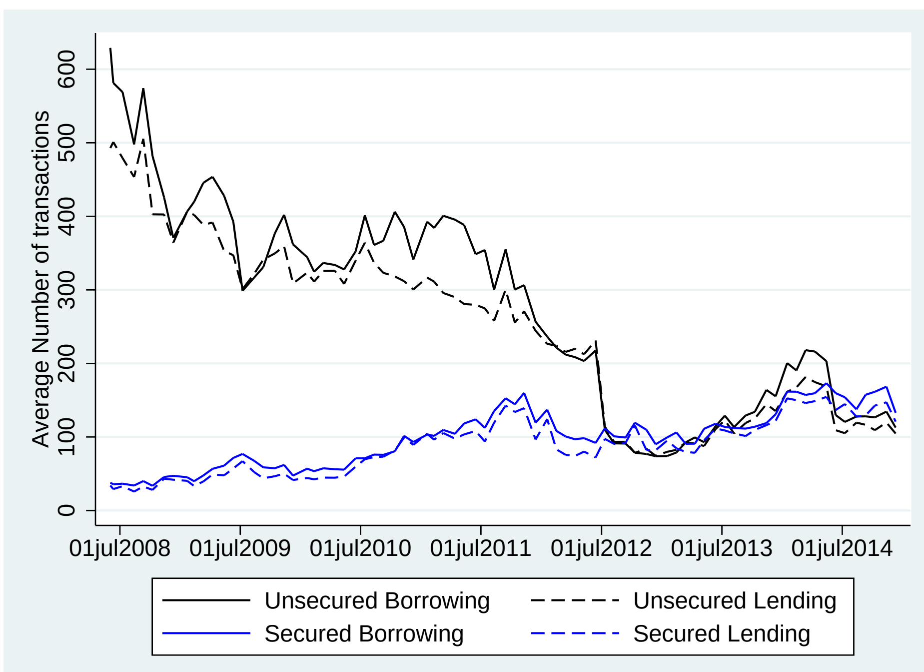

Figure IA.2. Number of money market transactions. The figure shows the daily averages within each reserve maintenance period from June 2008 to December 2014 of the number of transactions. The black (blue) lines refer to the unsecured (secured) market and continuous (dashed) lines refer to borrowing (lending), respectively.

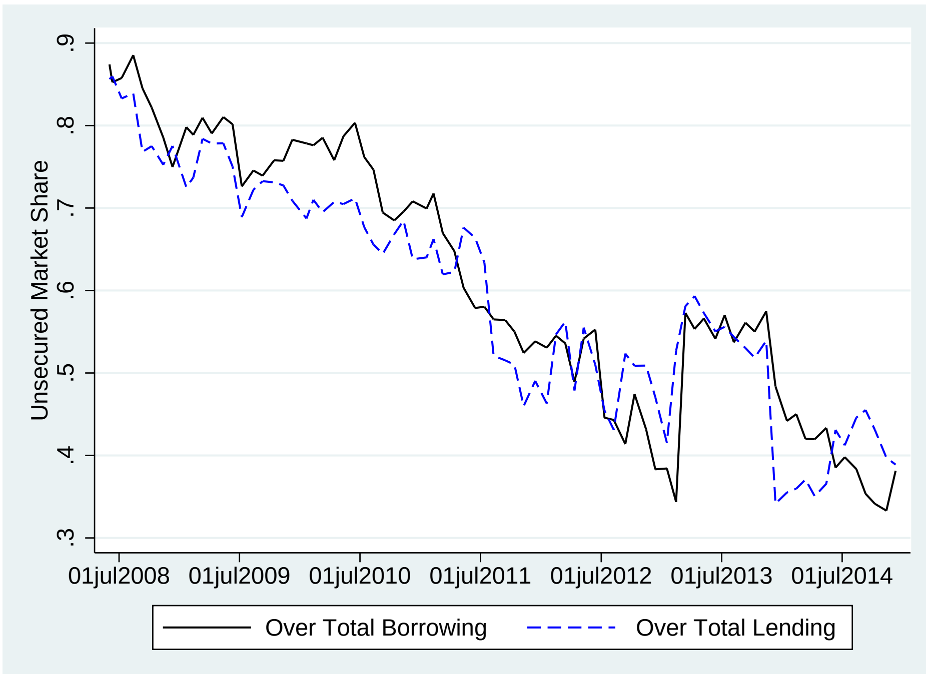

Figure IA.3. Unsecured Market Share. The continuous and dashed lines show the unsecured borrowing share over total borrowing and the unsecured lending share over total lending, respectively. Shares are computed as daily averages within each reserve maintenance period from June 2008 to December 2014.

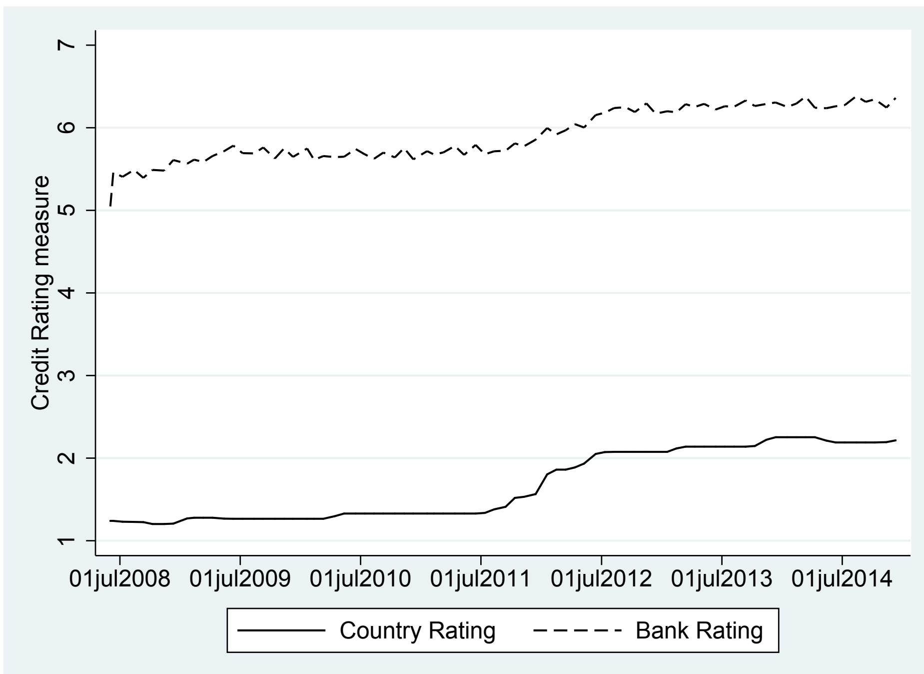

Figure IA.4. Average Ratings. The figure shows the average country and bank-specific ratings across reserve maintenance periods (RMPs) from June 2008 to December 2014. The rating is based on a homogenized scale ranging from 1 (best, or AAA/Aaa) to 25 (worst) across Standard & Poor's, Fitch, and Moody's.

Table IA.1
Interest Rate Spreads for Unsecured Lending

This table shows the panel regression results for lending spreads in the unsecured market. The depended variables is the volume-weighted spread for unsecured lending across the reserve maintenance periods (RMPs) for bank i in RMP t. The spread at time t is computed as the rate of bank i minus the volume-weighted market average rate at t. The dependent variables are regressed on a measure of credit risk based on banks' credit ratings. Column (1) reports the regression results without including any controls or fixed-effects. Columns (2) to (4) include different combinations of bank-specific as well as market-wide control variables and fixed effects. The bottom of the table shows the number of observations, the number of banks, and the regression R-squares. Robust standard errors (clustered at the bank level) are reported in parenthesis. Significance at 1%, 5%, and 10% is denoted by $***$, $**$, and $*$, respectively.

	$Spread_{i,t}^{UMM,lend}$			
	(1)	(2)	(3)	(4)
$CreditRisk_{i,t-1}$	0.00924	-0.00463	-0.00450	-0.00588
	(0.00580)	(0.00549)	(0.00551)	(0.00499)
$Size_{i,t-1}$			0.0212	0.0271
			(0.0241)	(0.0255)
$Leverage_{i,t-1}$			0.000367	-0.000190
			(0.000709)	(0.000510)
$Capital_{i,t-1}$			-0.00215	0.00138
			(0.00281)	(0.00187)
$ImpairedLoans_{i,t-1}$			8.38e-05	0.000132
			(0.000213)	(0.000201)
$Profitability_{i,t-1}$			-0.00383	-0.00904
			(0.00697)	(0.00656)
$ExcessReserves_t$				-0.0535
				(0.0322)
$MarketwideRisk_t$				0.00240
				(0.0270)
Constant	-0.0400	0.0198	-0.377	-0.488
	(0.0309)	(0.0281)	(0.492)	(0.507)
Bank FE	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	No
Observations	3,991	3,991	2,661	2,661
Number of banks	70	79	55	55
R-squared	0.007	0.161	0.154	0.013

IA.2. Further Robustness analyses

IA.2.1. Lending with forward looking measure of credit risk

The incentives to hoard liquidity increase when a bank's credit risk increases. Therefore, in the main regression we include past proxies of credit risk (in $t-1$). However, our results remain quantitatively unchanged when using forward looking measures of credit risk (in $t+1$). Results are shown in Table IA.2.

IA.2.2. Dynamic panel regression

Table IA.3 shows regression results when including lagged dependent variables to account for persistence in money market variables. Also in this dynamic panel equation we find a significant effect of credit risk consistent with our main regression results.

IA.2.3. Alternative measures of risk

Table IA.4 shows regression results when using the worst instead of the average rating across the three rating agencies. Results are qualitatively similar. We also repeated the analysis using country ratings and lagged UMM borrowing spreads – both are not significant. This is intuitive, because a country rating is a much rougher proxy than individual bank ratings and, as we see in our main results, borrowers with higher credit risk mostly face quantity rationing rather than higher spreads.

Table IA.2
Lending Volume

This table shows the panel regression results for money market lending volumes when using leading information on credit risk. The depended variables are the average daily bank's volume of total, unsecured, and secured lending across the reserve maintenance periods. The dependent variables are regressed on a forward looking measure of credit risk based on the banks' credit ratings. Column (1) reports the regression results without including any controls or fixed-effects. Columns (2) to (4) include different combinations of bank-specific as well as market-wide control variables and fixed effects. The bottom of the table shows the number of observations, the number of banks, and the regression R-squares. Robust standard errors (clustered at the bank level) are reported in parenthesis. Significance at 1%, 5%, and 10% is denoted by $***$, $**$, and $*$, respectively.

	Total				UMM				SMM			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$CreditRisk_{i,t+1}$	28.10	89.57	137.2	105.2	-147.6	-228.8***	-257.8**	-294.2**	175.7	318.3	395.0	399.4
	(192.9)	(279.4)	(361.4)	(364.3)	(99.84)	(85.10)	(101.1)	(113.9)	(171.9)	(269.4)	(347.0)	(347.8)
$Size_{i,t-1}$			-438.3	-467.0			-216.2	-272.5			-222.1	-194.4
			(311.9)	(352.4)			(218.1)	(219.6)			(229.7)	(263.5)
$Leverage_{i,t-1}$			18.26	14.37			8.943	7.107			9.322	7.265
			(12.02)	(11.10)			(6.849)	(5.671)			(9.233)	(8.836)
$Capital_{i,t-1}$			24.15	10.74			14.45	-8.942			9.698	19.68
			(19.68)	(19.70)			(12.71)	(13.12)			(16.82)	(15.14)
$ImpairedLoans_{i,t-1}$			8.880	8.659			3.350	2.856			5.531	5.803
			(6.602)	(6.091)			(3.443)	(3.128)			(5.640)	(5.313)
$Profitability_{i,t-1}$			-79.91	-85.30			-26.22	-29.69			-53.69	-55.61
			(95.95)	(78.04)			(34.48)	(24.83)			(92.18)	(70.19)
$ExcessReserves_t$				-951.5**				-438.3**				-513.2
				(369.9)				(177.9)				(322.3)
$MarketwideRisk_t$				511.7**				369.4**				142.3
				(225.2)				(166.6)				(144.5)
Constant	469.7	459.5	8,254	8,592	1,122*	1,844***	6,029	7,127	-652.2	-1,384	2,226	1,465
	(999.4)	(1,445)	(5,607)	(6,114)	(619.0)	(503.5)	(4,391)	(4,528)	(836.0)	(1,346)	(3,579)	(3,797)
Bank FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No
Observations	6,241	6,241	3,728	3,728	6,241	6,241	3,728	3,728	6,241	6,241	3,728	3,728
Number of banks	79	79	61	61	79	79	61	61	79	79	61	61
R-squared	0.027	0.055	0.090	0.085	0.019	0.103	0.132	0.112	0.027	0.055	0.090	0.085

Table IA.3
Lagged dependent variables

This table shows the panel regression results for money market volumes and spreads when including lagged dependent variables. The dependent variables are regressed on a measure of credit risk based on the banks' credit ratings as well as bank-specific control variables. The bottom of the table shows the number of observations, the number of banks, and the regression R-squares. Robust standard errors (clustered at the bank level) are reported in parenthesis. Significance at 1%, 5%, and 10% is denoted by $***$, $**$, and $*$, respectively.

	$Volume_{i,t}$				$Spread_{i,t}$			
	Borr UMM (1)	Borr SMM (2)	Lend UMM (3)	Lend SMM (4)	Borr UMM (5)	Borr SMM (6)	Lend UMM (7)	Lend SMM (8)
$LaggedDependentVariable$	0.789***	0.706***	0.869***	0.894***	0.345***	0.312***	0.482***	0.255***
	(0.0266)	(0.0295)	(0.0259)	(0.0443)	(0.0672)	(0.0457)	(0.0561)	(0.0616)
$CreditRisk_{i,t-1}$	-29.10***	57.76***	-10.58*	41.02*	0.00633*	-0.00328*	-0.00178	0.00350
	(10.45)	(14.33)	(6.166)	(23.60)	(0.00351)	(0.00194)	(0.00316)	(0.00352)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,749	3,749	3,749	3,749	2,627	1,992	2,541	1,895
Number of banks	61	61	61	61	51	58	51	58
R-squared	0.709	0.546	0.800	0.813	0.223	0.202	0.352	0.162

Table IA.4
Worst credit rating

This table shows the panel regression results for money market volumes and spreads when using the worst case rather than the average of the three rating agencies. The dependent variables are regressed on a measure of credit risk based on the banks' credit ratings as well as bank-specific control variables. The bottom of the table shows the number of observations, the number of banks, and the regression R-squares. Robust standard errors (clustered at the bank level) are reported in parenthesis. Significance at 1%, 5%, and 10% is denoted by $***$, $**$, and $*$, respectively.

	$Volume_{i,t}$				$Spread_{i,t}$			
	Borr UMM (1)	Borr SMM (2)	Lend UMM (3)	Lend SMM (4)	Borr UMM (5)	Borr SMM (6)	Lend UMM (7)	Lend SMM (8)
$CreditRisk_{i,t-1}$	-134.4**	180.7***	-172.6***	284.3	0.0131**	-0.00498	-0.00610	0.00223
	(66.03)	(55.43)	(51.88)	(247.1)	(0.00630)	(0.00406)	(0.00681)	(0.00683)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,749	3,749	3,749	3,749	2,703	2,201	2,661	2,110
Number of banks	61	61	61	61	53	59	55	58
R-squared	0.210	0.210	0.128	0.092	0.093	0.103	0.155	0.056