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Keywords: G01; G10; G21

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On the role of market makers for money market liquidity and tensions*

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Abstract

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1 Introduction

The ongoing financial crisis has highlighted the neuralgic role of the interbank market for the functioning of the financial system. The subprime crisis in the U.S. only turned into a global financial crisis because of the resulting dry-up of money markets. The evolving sovereign debt crisis in the Euro area in 2011/2012 was severely aggravated by tensions in interbank markets in particular by the national segmentation of those markets in the European Monetary Union.

Several reasons for this money market dry-up have been put forward and empirically assessed in the academic literature: Afonso et al. (2011) show that a jump in counterparty credit risks, as suggested by Flannery (1996), has played an important role for tensions in the U.S. federal funds market. Elevated informational asymmetries about conterparties' credit risk, proposed by Freixas and Jorge (2009), are shown to be a key driver for the money market dry-up after the onset of the financial crisis in 2007 by Abbassi et al (2014). On the other hand, precautionary liquidity hoarding, as modelled by Allen, Carletti, and Gale (2009), was pointed out as another potential cause for the market turmoil. Indeed, Acharya and Merrouche (2013) show for the U.K. that liquidity hoarding was a key reason for tensions in the interbank market. However, none of those approaches explicitly accounts for the micro structure of money markets despite the fact that several theoretical contributions highlighted that in search driven markets middlemen play an important role in facilitating transactions (see Rubinstein and Wolinsky (1987), Biglaiser (1993), Li (1998), Afonso and Lagos (2014)). Clearly, the over-the-counter nature of unsecured interbank trading qualifies this market as a search driven one. Indeed, there is strong evidence of a tiering structure in the interbank market, suggesting that some banks serve as money market makers (see Craig and von Peter, 2014). Therefore, given that market makers play an important role in money markets, it seems reasonable to expect that the ability of market makers to take positions and facilitate trades is also an important determinant for the functioning of this market. For instance, feedback effects from increased funding constraints and elevated funding risks of market makers as modeled by Gromb and Varyano (2004) and Brunnermeier and Pedersen (2009) might be present in the money market as well and might have contributed substantially to the tensions in this market during the recent financial crisis.

In this paper, we use a unique data set that comprises the trading book of the unsecured money market trading of one of the largest market makers in the Western hemisphere. We study the extent to which funding constraints and particularly funding liquidity risks accumulated by this market maker affect his pricing of liquidity and the realized bid-ask-spread he quotes. We measure the assumed funding liquidity risks by the deviation of the maturity mismatch of outstanding interbank loans and deposits from its long-term average, assuming that this average captures the 'target' maturity mismatch. We then regress the rate the market maker charged for his interbank loans and deposits as well as his realized bid/ask spread against his assumed funding liquidity risk. Contrary to the credit risk spread, the funding liquidity risk is an unobservable variable for market participates when lending and borrowing from the market maker. Furthermore, for each transaction, we control for the counterparty's characteristics using an official credit rating, counterparty fixed- and relationship effects. Moreover, we include the market-wide credit risk premium and changes in the net money market funding demanded by the market maker.

Our results provide four key insights: First, the larger the funding liquidity risk assumed by the market maker, the higher the market price for liquidity (the price the market maker pays for deposits and the rate he charges for loans). Thus, the market maker seems to hoard liquidity in response to a higher liquidity risk exposure. Second, with a higher accumulated funding liquidity risk, the marker maker has a higher term premium (longer term loan *and* deposit contracts require a higher interest rate when compared with respective shorter contracts). As a consequence it becomes pricier for other market participants to hedge their liquidity risk through transactions with the market maker. Third, the market liquidity – measured by the realized bid-ask-spread quoted by the market maker – deceases significantly as the retained funding liquidity risk of the market maker increases. Thus, transaction costs for participants in the unsecured money market increase and the efficiency of the liquidity reallocation within the banking system is impaired. Forth, the realized bid/ask spread rises substantially for longer-term loans and deposits if the market maker's close-of-business-day liquidity risk increases, while such an increase has much less of an effect on short-term contracts. This suggest that particularly in the term segment of the money market, market liquidity and transaction costs depend on the market maker's funding risks. As a further interesting result, we find some evidence that a deterioration in the market maker's own perceived credit quality (measured by his publicly observable credit risk) for the post-August 2007 crisis period not only required him to pay a higher risk premium on deposits received from the interbank market, but that he also charged a mark-up on loans granted in response to increases in his idiosyncratic credit risk. Apparently, the market maker rolled over a part of his own elevated funding costs to his borrowers. In sum, we find along various dimensions a detrimental effect of the market maker's assumed funding risks and funding costs on the price for liquidity on the one hand and the market liquidity in the unsecured money market on the other hand. An increasing price of liquidity, a deteriorating money market liquidity, and higher costs of hedging maturity mismatches is likely to increase banks' sensitivity to liquidity risk exposures. Therefore, these documented effects have the potential to give rise to adverse liquidity spirals as suggested in Brunnermeier and Pedersen (2009).

These results have important policy implications. On the one hand, they might suggest that apart from higher capital requirements, money center banks – as systemically important financial institutions – should also be required to hold larger liquidity buffers, in particular to maintain a higher liquidity coverage ratio. On the other hand, our results also show that the ECB was well advised to not only provide additional liquidity to the banking system, but to provide it at longer-term maturities through LTROs since these mitigated the accumulated liquidity risks of money market makers, thereby lowering the spread between the unsecured and secured interbank rates and fostering the liquidity in the unsecured money market.

2 Related Literature

Our paper is related to several strands of the literature. It builds on the discussion about key frictions in money markets and the extent to which frictions contributed to the tensions prevailing in this market after the failure of Lehman Brothers and the sovereign debt crisis in the Euro area. Previous work stresses informational asymmetries in the money markets as a main driver for the turmoil: Freixas and Jorge (2009) argue that uncertainty about counterparties' credit worthiness generates a lemons problem in interbank market. Acharya and Skeie (2011) and Heider, Hoerova and Holthausen (2009) show that banks hoard liquidity and reduce term lending in anticipation of being rationed in the interbank market (or unable to roll-over short-term debt) which leads to a shortfall of liquidity supply. Allen, Carletti and Gale (2009) argue that market incompleteness (due to informational asymmetries about liquidity needs) also generate inefficient liquidity hoarding in the presence of aggregate uncertainty. Those models all assume a centralized interbank market. But in practice, money markets have an over-the-counter (OTC) structure and hence, this assumption seems not necessarily appropriate for this market. Thus several recent contributions such as Afonso and Lagos (2013) model the unsecured money market as a decentralized market with search frictions.

However, a large strand of the theoretical literature emphasizes that in search driven OTC markets, the microstructure and in particular middlemen serving as market makers, play an important role. Rubinstein and Wolinsky (1987) show that middlemen enhance efficiency in an OTC market, given that they facilitate search. Biglaiser (1993) finds that in an OTC market with a lemons problem, the middlemen with a better screening technology improve efficiency. Li (1998) shows that middlemen emerge endogenously in an OTC market with lemons problems and a screening technology. However, none of those models takes into account that the ability of market makers to assume positions, to facilitate trade, and to provide market liquidity might be restrained. Lagos, Rocheteau, and Weill (2011) show that even middlemen without financial constraints provide only limited liquidity as their own liquidity risk grows. While Gromb and Vayanos (2004) and Brunnermeier and Pedersen (2009) neglect the OTC market structure with search frictions in their models, they show that funding restraints and funding risks of market makers are important determinants for asset market liquidity. They also show that deteriorating market liquidity aggravates market makers' funding constraints, impairing market liquidity further. Using the trading book of a key market maker in the unsecured European money market, we are able to empirically assess whether changes in the funding constraints and funding risks of the market maker indeed affect his liquidity provision to the money market.

Knowing the exact source of frictions that prevail in the interbank markets and contributed to the financial crisis is of upmost importance for monetary policy makers since the effectiveness of the policy measures depend on the particular source of the friction(s): If indeed liquidity hoarding was the key driver, then additional liquidity supply would be appropriate and sufficient to mitigate tensions in the interbank market. If counterparty credit risk or elevated uncertainty about it lead to the dry-up, then measures to recapitalize banks and to foster trust in their solvency are key. If search frictions and market makers are important and their funding restraints matter for pricing and the liquidity of funds in the money market, the measures that primarily aim at mitigating those constrains are particularly effective. Thus, several papers empirically assess the the role of different frictions. Acharya and Merrouche (2013) and Ashcraft et al. (2011) find evidence for liquidity hoarding in the U.K. and U.S. money market, respectively. Similarly, Angelini, Nobili, and Picillo (2011) report that risk aversion led to a dry-up of liquidity supply in the Italian interbank market. Afonso et al. (2011) report evidence for the federal fund market that the stress in the market was solely due to an elevated credit risk. Braeuning and Fecht (2012) and also Abbassi, Brauning, Fecht and Peydro (2014) find that informational asymmetries about counterparty credit risks was a crucial driver of the dry-up in the Lehman crisis as well as in the sovereign debt crisis in the Euro area. But to the best of our knowledge no study has addressed up to now the question to what extent the microstructure and in particular strains on market makers severely amplify tensions in the money market and thus contributed to its dry-up. This is surprising given that Ashcraft and Duffie (2007) and Afonso, Kovner, and Schoar (2013) find evidence for the importance of search frictions in the federal funds market and that Craig and von Peter (2014) at the same time also show that money center banks play an important role as market makers in this market. Based on the trading book data of a single market maker in the unsecured money market we try to fill this gap. Obviously such an analysis would also be feasible using the bilateral interbank transactions extracted from payments data (as used for instance in Afonso et al (2011) Braeuning and Fecht (2012) and Abbassi, Brauning, Fecht and Peydro (2014)). While this data would also permit to analyze the behavior of different intermediaries and their interactions, this data does not comprise transactions with fairly small banks that have no access to the payment system, in particular small foreign banks or non-Euro zone banks. For those banks, however, it is likely that search costs are particularly high and hence, a market maker therefore particularly important for their market access. Thus, while using our data for this analysis has a drawback since we are missing a cross-section of market makers, our data has the advantage of providing for a single market maker his entire trading activity in the unsecured market, also with all small and foreign banks.

While to the best of our knowledge there is no paper studying the empirical relevance of funding risks and funding constraints of market makers in the unsecured money market, there are a number of papers assessing these effects empirically in other financial markets. Most prominently, Comerton-Forde et al (2010) show that the larger the positions market makers hold in the New York Stock Exchange and the larger capital losses they incur are, the higher the bid/ask spreads the respective market maker quotes and the higher the spread prevailing in the stock market in which the market maker is active. Karnaukh et al. (2015) show how the market liquidity on the foreign exchange market is related to funding liquidity and constraints of FX sport dealers. Thus, their results are very much in line with our findings for a very different market though. Further papers - which however also focus on stock markets - are Anand, Irvine, Puckett, and Venkataraman (2013) and Hameed, Kang, and Viswanathan (2010).

3 The market maker and data construction

3.1 The market maker

Our analysis is based on data comprising the unsecured money market trading book of one of the major banks in Germany. This bank is also a key player and market maker in the money market in the Western world. All trades were arranged from the global headquarter of the bank in Germany and most of the trades originate from the Western European region. However, we also observe a significant amount of transactions with banks from Eastern Europe, the Middle East, and the United States (Eastern Coast). Only a minor part of the transactions were with German counterparties. Indeed, the first German counterparty in terms of trade frequency ranks at place 47 (for a total of 450 banks in the original data set).[1] Overall there seems to be no preferred region in which the market maker trades. On average, three traders transacted with one counterparty. For counterparties with which the market maker transacted frequently, up to eight traders were involved in trading activities. Hence, clients with which the market maker transacted were not served by a single designated trader but instead, each trader could seemingly trade with any counterpart. Over the sample period 2007/2008, the bank had a stable high-grade credit rating.[2]

3.2 Data set

The data set initially comprises 20,670 transactions for the time period 02. January 2007 to 31. December 2008. It includes the capture date and a time stamp (Central European Time, CET) for each trade, the contractual agreed interest rate in basis points, the trade amount in Euro, the value and maturity date and time, the type of transaction (interbank deposit or loan), name of the counterparty and type of the counterparty (whether it is a central bank or a private bank). The data set also allows us to match the name of the trader to each transaction.

For some transactions, the value date and capture date didn't match, meaning that the trade was not recorded at the correct date and time. We decided to drop those observations. Furthermore, some transactions were with central banks, whereby the market maker participated in the weekly main refinancing operations and accessed the marginal deposit facility (MDF) of the Eurosystem. We drop these observations since the price on the MDF is set exogenously by the central bank. The same holds for the weekly main refinancing operation starting in October 2008. Moreover, the bank has to pledge collateral when borrowing liquidity in the main refinancing operations and thus, the nature of these transactions is not unsecured. Thus,

[1] In terms of trade amount, two German banks rank amongst the top ten counterparties. Running our main specification with the largest 60 counterparts by traded volume only would not change our findings.

[2] The money market operations of the market maker are also considerable in terms of size: Relative to the average amount that the bank drew in the Eurosystem's weekly main refinancing operations (MROs), the average size of a transaction in the money market amounted to one-tenth of the amount of an average MRO transaction. Note that the Eurosystem provides MRO liquidity to the banking system to allow banks to satisfy their minimum reserve requirements which amounted to 2% of banks' highly liquid liabilities.

our final sample consists of 17,721 trade observations. Since we analyze the evolving positions of the bank, we need a unique time identifier for each transaction. Since the time stamp on the capture date only records minutes but not seconds, the data set includes 1,365 duplicate time identifiers. If a duplicate time identifier occurred, the order of transactions is maintained as in the original data set but each duplicate is ordered one second after the trade with the first duplicate occurrence. The opposite ordering would not alter the results for the fully-specified models.

3.3 Variable construction

To set up our pricing equation, we first construct a risk-free benchmark interest rate: in order to capture general changes in the money market rates - for instance due to monetary policy interventions - we decided to use the *Eurepo* as the risk-free benchmark rate. The Eurepo rates are obtained from a panel survey of banks, where banks can submit a rate by 11.00 a.m. CET to Brussels. The key difference between the Eurepo and the Euribor is that the Eurepo covers rates for collateralized interbank lending while the Euribor rate comprises uncollateralized interbank loans. Thus, while the Eurepo measures only the price for liquidity for different maturities, the Euribor also captures the general credit risks as perceived by market participants. The bank from which we obtained the trading book is part of the Eurepo and the Euribor panel. We prefer the Eurepo as the benchmark rate since this allows us to analyze the market wide credit risk separately. We will also run the fully specified model with the Euribor as a robustness check. In order to mitigate endogeneity concerns, we lag the Eurepo and Euribor rates by one day.[3] We match the appropriate maturity of the Eurepo (Euribor) benchmark rate to each transaction in the data set and use the following maturity brackets: for overnight loans and deposits, we use the Eurepo overnight (TN) rate. The 1, 2, 3 week and the 1, 2, 3, 6, 9, 12 months Eurepo rates are used for the term lending transactions. We do not interpolate between these rates and use the next lower maturity bucket for matching. Our results do not depend on whether we use the next lower or higher maturity bucket for the maturity matching.

From the trading book, we construct the variable *Maturity* as the length between the time on the capture date when the transaction was initiated and the close of the transaction at 7:20 p.m. CET on the maturity date. Secondly, *Amount* enters the regression directly from the trading book (in Euro millions). Thirdly, to account for possible relationship influences between the bank and its counterparties, we define a dummy variable, *Relationship banking dummy*, which is equal to 1 if the bank was involved in a trade with the same counterparty and transaction type over the previous 50 transactions which equals around two business days.

We matched the trading book data at the transaction level with external data sources: First, we merged each counterparty's credit rating to the respective transaction by creating a

[3]This doesn't solve all endogeneity concerns since the market maker is part of the Eurepo and Euribor panel. However, if we were to use the monetary policy rate (minimum bid rate in the main refinancing operations) set exogenously by the European Central Bank instead of the Eurepo, our results would remain robust with respect to our main variables.

categorial variable *Counterparty credit rating* with the following aggregated categories: AAA, AA, A, BBB, BB, B, CCC, and Not Available (N/A). The ratings were obtained at an end-of-day basis from Fitch, Standard & Poor's and Moody's. For the main regressions, we use the lowest credit rating provided by any of the three rating agencies. Since we can match real-time credit ratings only to around half of our transactions and given that official ratings change rather slowly and thus have a low frequency, we construct quarterly counterparty fixed effects as a substitute for the official credit ratings for the fully-specified models. Next, we include the credit risk of the market maker. Although credit default swap (CDS) contract data with a five-year maturity of the market maker is available on a daily basis[4], a significant liquidity premium - particularly in the crisis phases - may mask the true (intrinsic) credit risk. Since the market maker has publicly listed shares outstanding, an implied (or intrinsic) credit risk spread based on a Merton-type model approach can be calculated. For this paper, we revert to the five-year implied credit risk spread calculated by Bloomberg's default risk assessment function (DRSK).[5] Third, as a measure for the aggregate counterparty credit risk prevailing in the money market, we include the variable *3 months Euribor - Eurepo* spread which is the difference between the three month unsecured interbank rate minus the three month secured interbank rate.

Our key variable of interest is the unsecured funding liquidity risk, LIQ. This variable is unobservable for market participates when lending and borrowing from the market maker. It captures - after each trade - the deviation of the current maturity mismatch of outstanding interbank loans and deposits from the mean maturity mismatch ($\bar{m}$) the bank runs on its interbank trading book. It is calculated as

$$LIQ_{t+i} = \sum_{C=0}^{t+i}(m_C^l - \bar{m})V_C^l - \sum_{C=0}^{t+i}(m_C^d - \bar{m})V_C^d, \tag{1}$$

whereby m_C^l and m_C^d is the remaining maturity in days at $t+i$ of all outstanding loans and deposits, respectively.[6] These are loans and deposits with a capture date C at the current point in time $t+i$. The respective remaining maturities are normalized with the current average outstanding maturity, $\bar{m}$, across all outstanding deposits and loans granted at time $t+i$. This way, only loans with a maturity larger than the currently outstanding average maturity and

[4]Data on the six-months or one-year CDS for the market maker were not available for each business day and the true credit spreads are likely to be overshadowed by a potentially large liquidity premium on the days on which data is available. This problem becomes even larger after the onset of the financial crisis in August 2007.

[5]Bloomberg applies a hybrid model to calculate the five-year implied credit risk spread: It builds on a Merton-type framework and uses adjusted accounting data and the share price of the bank as model inputs. The correlation between the five-year implied credit risk spread calculated by Bloomberg and the five-year market-traded CDS spread is 0.86. Since a five-year horizon is rather long for money market transactions, we use the one-year default probability calculated by Bloomberg as a robustness check. Note that Bloomberg uses the one-year default probability as one input parameter in their assessment of the five-year implied credit risk spread.

[6]This implies that we assume that all trades are settled at 7:20 p.m. on the maturity date. Specifying an earlier maturity time would not change our results.

deposits with a maturity below the currently outstanding average maturity add to the funding liquidity risk measure. In the main specification, each maturity enters the calculation of $\bar{m}$ on an equal-weighted basis, irrespective of the traded amount. As a robustness check, we calculate $\bar{m}$ by weighting each maturity of an outstanding transaction by its traded amount relative to the total outstanding amounts at $t + i$.[7]

It is reasonable to assume that the risk tolerance changed over time in particular in response to the crisis. Since this would imply a level shift in our LIQ_{t+i}, we partially control for this by including time fixed effects. Our measure also implies that a loan can migrate from liquidity risk contributing to liquidity risk mitigating if its maturity falls below $\bar{m}$ (and vice versa for deposits).[8] LIQ_{t+i} is re-calculated after each transaction and is used as an explanatory variable for the pricing of subsequent loan or deposit trades. This however not only assumes that the liquidity risk is managed continuously on an aggregate level but it also implies that the assumed liquidity risk is instantaneously known to each trader after each transaction. To relax this assumption, we also calculate the liquidity risk on a daily basis: LIQ_{daily} is equal to the funding liquidity risk at the close of business on the previous trading day. By using this specification as an explanatory variable for the pricing of subsequent loan and deposit trades, we assume that the funding liquidity risk level is communicated to all traders either at the beginning of the next trading day or at the end of the current trading day.

Finally, one might have the notion that the amount of funding received and needed from the unsecured money market is what actually drives the pricing of the loans and deposits and that our funding liquidity risk indicator actually only picks up this effect. In order to control for this, we construct an indicator for the net unsecured money market funding, *NMMF*, which is the difference between the currently outstanding deposits and the outstanding loans:

$$NMMF_{t+i} = \sum_{C \leq t+i}^{M} V_C^d - \sum_{C \leq t+i}^{M} V_C^l. \tag{2}$$

whereby C (M) is the capture (maturity) date of the respective contract and V_C^l (V_C^d) is the respective volume of the outstanding loans (deposits).

Thus, while the liquidity risk indicator provides a forward looking perspective, the *net money market funding* indicator draws a contemporary picture of the gap between total deposits and total loans outstanding at $t + i$.[9]

[7]We tried various other sensible specifications for $\bar{m}$, including (i) the average maturity $\bar{m}$ calculated over the whole sample period, where we assume that the bank targets a certain mean-maturity mismatch over time, (ii) the rolling mean of the average outstanding maturity $\bar{m}$ at at time $t + i$, (iii) excluding the upper 1% of the maturity distribution for the calculation of $\bar{m}$. The results for the funding liquidity measures for the fully specified model remain consistently significant.

[8]Note that our approach follows the maturity-related measure for liquidity risk proposed by Berger and Bowman (2009). However, our approach is obviously much more granular, as it is based on the *remaining* maturity.

[9]Our constructed funding liquidity risk (LIQ) and the net money market funding (NMMF) indicators follow closely to what has been implemented in the treasury departments of major German banks. The following

4 Descriptive statistics

In our final sample, we have 436 counterparts with which the market maker transacted. The median number of observed transactions per single counterparty is 11. The bank traded with 70 counterparts only once.

Tables 1, 2 and 3 outline some descriptive statistics for our main variables. Table 1 provides different percentiles and the standard deviation of all explanatory variables, except for two credit risk measures which are not shown due to confidentiality reasons. Noteworthy is that the variation in the contractual agreed *Fixed rate* is much lager than the variation in the Eurepo or Euribor. Moreover, both the funding liquidity risk and the net money market funding measures seem to display negative values for most observations. However, it should be noted that the median value of the funding liquidity risk measures is not statistically significant from zero. Hence, from a median perspective, the bank seems to target a funding liquidity risk of zero and we find this to hold across most of our different specifications for $\bar{m}$.

[Table 1 about here]

Table 2 depicts the total observations and the means of the three trading book entries with respect to the rating of the respective counterparties with which the bank traded. It should be noted that we can attach real-time credit ratings only to around one-half of all transactions and all numbers in the table only account for transactions for which at least one official credit rating was available. Using a standard t-test with unequal variances for the *Fixed rate*, we find that the mean rates the bank charges for loans are significantly higher than the mean rates the bank pays for a deposit intakes. Interestingly, the bank pays the lowest mean price for deposit intakes when trading with AAA-rated counterparts and the mean price has a tendency to increase as the credit worthiness decreases. Whereas the mean maturity of around 1.85 days is about equal between deposits and loans for AA and A-rated counterparts (most transactions occurred with counterparts from these rating buckets), a significantly different pattern emerges for the average traded amount: For both, deposit and loan transactions, the average traded size declines as the credit quality deteriorates. Moreover, the mean amount for a loan is about 10 times as large as the mean amount for a deposit transaction with an equal rating in the high-grad area, although the amount of deposits and loans converge to the same mean as the credit quality deteriorates.

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paragraph provides a short summary of what Deutsche Bank and Commerzbank (No. 1 and No. 2 in Germany in terms of balance sheet size) have implemented with respect to their liquidity risk management: (Net) liquidity and funding risks are steered by the treasury department, taking into account the liquidity risk structure for a one-year time horizon. Reporting systems are run on a daily basis, providing liquidity and funding risk information to the bank's branches and the headquarter. There is an operational liquidity risk management in place which is based on an intraday setting. Funding limits apply to (i) the cumulated global cash flows from the money market and to (ii) the total volume of unsecured funding from this market. See also: Annual Report 2013 of Deutsche Bank AG (pp. 184-191; March 2014): `https://www.db.com/ir/en/download/Deutsche_Bank_Annual_Report_2013_entire.pdfandAnnualReport2013ofCommerzbank` and the Annual Report 2013 of Commerzbank AG (pp. 126-127; March 2014): `https://www.commerzbank.de/media/aktionaere/service/archive/konzern/2014_2/Geschaeftsbericht2013_Konzern_EN.pdf`.

Finally, it is noteworthy that most of the rated counterparties for deposit and loan transactions stem from the AA and A-rated category.

[Table 2 about here]

Table 3 shows the structural differences between loan issuance and deposit intakes over time. For this purpose, we split the sample for the descriptive analysis in three distinct time periods: i) the tranquil (normal) phase starting on 2^{nd} January 2007, ii) the first crisis phase starting on 9^{th} August 2007, when BNP Paribas was forced to freeze three of its funds,[10] and iii) the second crisis period after the collapse of Lehman Brothers on 15^{th} September 2008 which pushed the Euribor to Eurepo spread to new all-time highs.

From these descriptive statistics it is interesting to note that only around 17% of all transactions were interbank loans, where the bank extended credit to another financial institution. Moreover, the difference between the price of loans to deposits was on average always positive and around 68% of all transactions were less than two days. There is no clear difference in the maturity structure of loans and deposits over time. The median maturity seems to remain pretty stable over time, although we note a slight increase in the average duration of a loan transaction in the after-Lehman collapse time period. Turning to the median amount traded, we clearly see that it is significantly higher for loan transactions across all time regimes. Taking these findings together, we conclude that the bank engages in its money market trades in lot size transformation and pooled deposits to issue loans and thereby profited from the average interest rate spread which was always positive across the different time regimes. This also indicates that the bank was indeed a market maker in the money market, making a profit though its trading activities rather than funding the liquidity needs of other business units. This is additionally supported by our finding that the median net money market funding is zero.

Looking at the mean rating distribution, one can clearly see that loans were on average granted to counterparties rated one to two notches higher when compared to the rating of counterparties that lent funds to the bank. However, we do neither for deposits nor for loans observe an increase in the average rating over time! Hence, we do not find that the bank increased its lending standards in the aftermath of the subprime crisis and the Lehman collapse. However, we do observe that the bank made less frequent loan trades in the market per trading day, although it did so with higher absolute amounts. These higher average amounts were however not sufficient to keep the issuance volume for loans to the money market on a stable level on an absolute basis. Indeed, we observe that the bank seemed to hoard liquidity by taking accumulated excess reserves to the marginal deposit facility (MDF) of the Eurosystem (overnight maturity). For the market maker's interbank borrowing, we observe that not only the amounts of the deposits increased over time but we also see that the market maker borrowed more frequently from the money market. In the empirical regressions, we include a dummy variable for the days on which the market maker deposited excess reserves at the MDF to see

[10] The three months Euribor-Eurepo spread, a measure for the sentiment of trading participants in the money market, shoot up to 100 basis points and remained at an elevated level for the remainder of the sample period.

whether deposits and loans are priced differently on those days. During the two sample years, a total of 33 traders conducted money market transactions for the bank. Of the 33 traders however, only 14 were trading over all sub-sample periods. We will control for trader-specific effects in the panel regression with trader-fixed effects.

[Table 3 about here]

Finally, we depict the evolution of the funding liquidity measures in Figure 1: The three graphs depict the evolution of three different specifications for LIQ: Sub-graph (a) depicts the evolution of LIQ, where the maturities of loans and deposits are normalized with the equal-weighted average maturity across all currently outstanding loans and deposits. This specification of LIQ is used for the main regressions. Sub-graph (b) depicts the evolution of LIQ, where the maturities of loans and deposits are normalized with the volume-weighted average maturity across all currently outstanding loans and deposits. Here, the maturity which is used to normalize the maturity of each loan and deposit is more heavily influenced (weighted) by larger-sized transactions. Finally, sub-graph (c) shows the end-of-day version of LIQ, where the maturities of loans and deposits are normalized with the equal-weighted average maturity across all currently outstanding loans and deposits.

[Figure 1 about here]

5 Methodology

5.1 Econometric strategy

In terms of econometric strategy, we will estimate two different types of econometric specifications for our models. First, we use a standard OLS regression of the form

$$y_i = x_i'\beta + u_i, \;\; i = 1, ..., N \tag{3}$$

However, our data set also allows us to construct two panel perspectives: First, we are able to identify the exact name of the counterparty which allows us to run a panel regression by tracking the name of the counterparty over time. In this paper, we use quarterly counterparty fixed effects to account for time-invariant counterparty-specific factors for each quarter which we couldn't otherwise include in our model. In particular, we use these fixed effects as a substitute for official credit ratings. Secondly, we can match the name of each trader to the respective transaction which allows us to split the interbank pricing of the bank itself into its components by accounting for the respective trader who was responsible for the conditions of the trade. This also allows use to capture trader-specific effects like time-invariant personality characteristics, attitudes to risk or time-invariant relationship banking effects. For the trader fixed effects regression, will estimate a standard panel model of the form

$$y_{jt} = \alpha_j + x'_{jt}\beta + u_{jt}, \quad t = 1, ..., T; \;\; j = 1, ..., N \tag{4}$$

where α_j is specified as the j's trader fixed effect.

5.2 Model specifications

For the key results, we estimate nine models by OLS. The dependant variable is the *Contractual Fixed Rate* in logs. In Model 1, we include the *Eurepo* in logs as the risk-free benchmark rate which serves as the pricing intercept for each transaction as well as the *Maturity* (in days), and the *Amount* (in Euro millions) of each trade.[11] In addition, we include the variable *Trade Type* which picks up the incremental effect of a loan transaction.

Model 2(a) and Model 2(b) introduce separately the funding liquidity measure, *LIQ* (in 100 billions Euros), and the net money market funding, *NMMF* (in billion Euros), lagged by one transaction.[12] Model 2(c) subsequently unites the LIQ and the NMMF into a single regression.

Model 3(a) includes the variable *Official Credit Ratings* (interacted by the Trade Type) to control for counterparties' credit quality. From Model 3(b) onwards, we additionally allow for *Monthly time fixed effects* to account for intertemporal changes in the mark-ups. Since official credit ratings transmit creditor relevant information only slowly, have a low frequency, and given that we can match real-time ratings only to around one-half of our observations, Model 3(c) includes *Quarterly counterparty fixed effects* instead of official credit ratings, interacted by the *Trade Type*.

In Model 4(a), an interaction term between *LIQ* and *Maturity* is included. While model 3(c) only allows to assess whether the market maker reacts to increases in the funding liquidity risks, Model 4(a) also allows to analyze whether he actively *manages* his funding liquidity risks: If the bank is willing to pay a higher price for an interbank deposit when its funding liquidity risk increased with the last trade *and* if it can secure a higher maturity for the deposit with the current trade, then the bank manages its liquidity risks actively.

So far, we made the strong assumption that the level of LIQ is communicated to each trader after each transaction. To allow for frictions in the coordination amongst traders during the day, we introduce a daily version of LIQ in Model 4(b).

Model 5 accounts for the one-day lagged credit risk spread of the market maker (*Bloomberg implied credit spread*). The higher the credit risk of the market maker, the higher the risk premium should be when the bank borrows from interbank market participants. As shown in

[11] Since our sample covers different monetary policy regimes and given that the price dispersion varies over time, we prefer to have the *Fixed Rate* and the *Eurepo* in logs. As a robustness check, we use both variables in their original measurement units later on. Our results do not depend on either specification.

[12] Market makers may set regret free quotes which would imply that it is not appropriate to lag the LIQ and NMMF indicators (see Madhavan et al., 1997). Using the non-one-observation-lagged versions of LIQ and NMMF would not change our findings for the fully specified model. However, given that we observe more than 13 traders for each time regime at the money market trading desk, we prefer to use the one-observation-lagged versions of LIQ and NMMF to allow for coordination amongst the traders once the trade has been executed.

Table 2, the market maker paid a higher price for deposit intakes from lower-rated counterparties. Similarly, we would expect that the market maker can (partially) roll over his increased refinancing costs due to his higher credit risk. In Model 9, we analyze whether the price effect of increases in the market maker's credit risk differs between deposits and loans.

Model 6 includes the one-day lagged *3 months Euribor-Eurepo spread* to account for market-wide (i.e. aggregate) increases in the counterparty credit risk and elevated systemic risk.

In Model 7, we account for *Relationship banking*. We expect that if the market maker conducted more frequent loan trades with a specific counterparty, he may demand a lower price. We interact the Relationship banking dummy with the Trade Type.

Model 8 analyzes whether the market maker charges a lower price for loan issues to other interbank participants if he has accumulated excess reserves. For this purpose, we use the market maker's access to the marginal deposit facility (MDF), where banks can revert at the end of a trading day to deposit their excess liquidity. Moreover, we can analyze whether the market maker has paid a higher price for deposit intakes on the days with an MDF access which would hint to liquidity hoarding.

Finally, in Model 9, we interact all variables of Model 8 (except for the MDF and Relationship variables) with the *Trade Type* to analyze the incremental price effect of a loan trade over a deposit trade. Our interest is on two variables in particular: First, we are interested in whether the market maker reacts differently in his pricing for deposits and loans if the funding liquidity risk increases. One might have the notion that an increase in the funding liquidity risk not only increases the price of loans and deposits but also leads the market maker to charge an additional price mark-up if he lends out liquidity. We test this by interacting *LIQ* and the *Trade Type* and analyze whether increases in LIQ lead to an additional (statistically significant) mark-up for the pricing of loans over the deposit pricing. Hence, we check whether his bid/ask spread increases if LIQ increases and see whether a higher accumulated funding liquidity risk of the market maker leads to a deterioration of the money market liquidity. Second, in Model 5, we assumed that the market maker does not react differently to changes in his idiosyncratic credit risk when pricing deposits and loans. However, the market maker may not be able to roll over increases in his own credit risk to the market. We test this by interacting the *Bloomberg implied credit risk* and the *Trade Type* to see whether the market maker is able to roll over increases in his credit risk to the market.

6 Empirical Results

Table 4 reports the results of our main models estimated by OLS for the time period January 2007 to December 2008. As regards to the standard pricing factors (Model 1), we find that the risk-free benchmark rate, *Eurepo*, is highly positively significant and of a plausible magnitude: If the one-day lagged Eurepo increases by 1%, the bank pays around 1.2% more for a deposit intake. If the market maker issues a loan, his price mark-up on the deposit price is an additional

0.05%.[13] Interestingly, the *Amount* of a transaction has no pricing impact. Thus, the market maker does not pay more or charge a higher price if he transacts for larger trade volumes. As expected, an increase in the *Maturity* has a positive impact. Each additional day in duration increases the price by 0.002%. Given that the 90% percentile for the maturity is 7 and 3 days for deposits and loans respectively, the economic impact of *Maturity* is overall rather limited. Note however, that the *Maturity* measure, as used in this paper, has to be interpreted as an add-on term premium, since we already matched an Eurepo rate with a maturity corresponding to the maturity of the respective trade to each transaction.

Turning to the key variable of interest (Model 2a), we find that the assumed liquidity risk faced by the market maker significantly affects the rate he pays for deposits and charges for loans. Thus, liquidity becomes pricier the higher the assumed liquidity risk of the market maker. Introducing the *Net money market funding* indicator in Model 2(b) shows that the standalone effect of this variable is insignificant. However, including *LIQ* and *NMMF* simultaneously, leads to the expected sign also for the *NMMF*. We will interpret the economic significance of these variables for the fully-specified Model 8.

In Model 3(a) to 3(c) we include the *Official Credit Ratings* (interacted by the Trade Type), *Monthly time Fixed Effects*, and *Quarterly Counterparty Fixed Effects* (interacted by the *Trade Type*) respectively. Most importantly, all explanatory variables remain consistently significant when including any of these factors. Note that including quarterly counterparty fixed effects and time fixed effects adds significantly to the adjusted R^2. The individual coefficients are not reported here for brevity.

Turning to the results of Model 4(a), we find that the inclusion of the interaction between *LIQ* and *Maturity* is insignificant. This implies that the bank is not willing to pay more for longer-term deposit and doesn't charge a higher price for a longer-term loan when it has accumulated an elevated level of liquidity risks. This implies that the market maker seems to not actively manage the maturity mismatch in his unsecured money market trading book. However, we so far made the strong assumption that the level of funding liquidity risk is communicated to all traders after each trade. This may be a strong assumption and we thus use the end-of-day version of LIQ and NMMF in Model 4(b), where we assume that all traders are informed either at the end or the start of a trading day about the current funding liquidity risk level and net money market funding. As the results of Model 4(b) show, not only do the coefficients of *LIQ* and *NMMF* increase in size and remain consistently significant, but we also find that the interaction between *LIQ* and *Maturity* is significantly positive. Hence, at least from an end-of-day perspective, the market maker seems to manage the maturity mismatch in his trading book actively. This implies that it becomes pricier for other market participants to offload liquidity risks with the market maker, the higher his assumed liquidity risk already is.

[13] Note that the regression output gives a coefficient above 1 for both, the deposit and loan regressions in all regressions. This is reasonable due to the fact that we do not interpolate between the Eurepo rates and use the next lower maturity for matching. When including credit risk measures or time fixed effects, the Eurepo pricing effects approach a coefficient of approximately 1.

In Model 5, we find that an increase in the market maker's own credit risk - as measured by the Bloomberg implied credit spread - leads to a higher pricing of deposits and loans. As we will show in Model 9, this significantly positive effect holds for deposits and loans, although the effect for loans is less pronounced. Taken together, these results suggest that the market maker has to pay a price mark-up on deposit transactions in the interbank market if his publicly observable credit risk increases. Moreover, he can pass part of the higher refinancing costs due to his increased credit risk back to the market.

Turning to Model 6, we find that an increase in the market-wide credit risk (3 months Euribor - 3 months Eurepo) leads to a significant increase in the pricing of interbank transactions. Thus, in addition to the borrower-specific credit risk, this measure of systemic risk also matters for the pricing of interbank liquidity. As we will show in Model 9, this significantly positive effect holds for both, deposit and loan transactions, although the positive effect for loans is more pronounced.

Turning to the *Relationship* results of Model 7, we find that the market maker pays a lower price for deposit intakes from banks that recently supplied funds to the market maker (over the past 50 transactions in one Trade Type). However, for loans granted, the market maker charges a higher rate to borrowers that recently received funds from him. Since we cannot model the factors responsible for the individual credit decision of the market maker, this effect might result from a selection effect: relationship borrowers might still get credit from the market maker but had to pay a markup on the lending rate (see Braeuning and Fecht (2012) for a more detailed analysis of this). But it might also be an indication for a hold-up (see Acharya et al., 2008). The selection problem should, however, at least partly be mitigated by the use of counterparty fixed effects which would - at least on a quarterly basis - control for any time invariant counterparty characteristics. Moreover, as we will show in the robustness section, relationship effects seem to play a more prominent role towards the end of our sample period.[14]

In Model 8, we analyze the effect on the pricing of loans and deposits on days on which the market maker accumulated excess reserves that he took at the end of the business day to the marginal deposit facility. It should be noted that we observe this behavior only towards the end of our sample. Turning to the results, we find that the market maker was willing to pay a higher price for deposit intakes on the days on which he accumulated excess reserves which implies that the market maker hoarded liquidity. Concerning the price effect for loans, we find that higher excess reserve holdings significantly decrease the price the market maker charges. Note that these are the add-on effects of holding excess reserves at the end of the business day, after controlling for the market maker's funding position, the market-wide credit risk, etc.

[Table 4 about here]

[14]Specifying a higher duration for the business relationship would alter these findings to insignificant. Indeed, the institutional set up of the market maker does not attach a designated trader to each counterparty but instead traders of the market maker transact across all clients which makes it more difficult for relationship lending to build up in the long-run.

Before discussing the results of the difference-in-difference analysis, we outline the economic significance (or relative importance) of the main terms of Model 8 using the Shorrocks-Shapely value decomposition of the R^2. This allows us to analyze the contribution of each individual pricing term, although the methodology neglects the interaction terms.[15] The first two columns of Table 5 show the contribution of each pricing factor to the model fit for the total sample. We find that the top four pricing factors are the Eurepo, the 3M unsecured-secured interbank rate, the Bloomberg implied credit risk, and the Funding liquidity risk which explain 72%, 13.9%, 4.4%, and 1.9% of the explained variance respectively. We thus conclude that the funding liquidity risk measure makes a significant economic contribution to the pricing of money market trades. In this context, it is interesting to analyze whether the economic significance of the predictors changed over time. For this purpose, we split the sample in a normal time period (January to August 2007, see Robustness Check 5a) and a crisis phase from August 2007 to December 2008 (see Robustness Check 5b). The results are depicted in the last four columns of Table 5: Interestingly, LIQ explains 12.5% of the explained variation in the tranquil time period, whereas all credit risk measures taken together explain a much lower portion. In the crisis phase however, the market wide credit risk explains next to the Eurepo most of the model fit. LIQ is however still an important factor in the pricing of transactions: Its economic significance amounts to that of the Trade Type and as we will show in the robustness section, the *LIQ x Maturity* interaction (and thus the active management of the funding liquidity risk) becomes a priced term in the crisis phase which is not accounted for in the Shapely decomposition. All in all, funding liquidity risks seem to play a very significant role in the pricing of interbank transactions in normal times. In the subprime and Lehman crisis phase, credit risks are the key component that makes up the price of money market transactions but liquidity risks are still an economically priced factor.

[Table 5 about here]

To see whether a higher accumulated funding liquidity risk level of the market maker leads to a deterioration of the money market liquidity, we next study the effect of a change in *LIQ* on the realized bid/ask spread that the market maker quotes. In order to do so, we run a difference-in-difference regression by interacting our key explanatory variables with the dummy variable for the Trade Type (which equals one if the trade was for loan and zero if it was for a deposit). This not only permits us to calculate the price difference (price delta) between loans and deposits, but also allows use to analyze whether this price difference increases if the value of an explanatory variable increases.

The regression results for Model 9 in Table 6 show that the regression line for loans slopes higher for every unit increase in LIQ than the line for deposits. However, the *price difference* between loans and deposits may or may not be significantly increasing over varying levels of the market maker's funding liquidity risk. The purpose of Table 6 is to analyze this issue: It

[15] Using a sample which is about the same in terms of the official credit rating or using Model 2(c) (in which we did not include any interactions) would not significantly change the consistency (order) of our findings.

depicts the loan-to-deposit price difference over the whole range of observed funding liquidity risk levels. As it can be seen, the difference between the mark-up on a loan transaction compared to a deposit transaction in response to a rise in LIQ is considered statistically significant across the whole universe of funding liquidity risk levels.

A rising value of the price difference implies that the the gap between the deposit and loan price increases, the higher the funding liquidity risk is. This in turn implies that the bid/ask spread widens as LIQ increases. Hence, very much along the lines of Brunnermeier and Pedersen (2009), we find that a higher funding liquidity risk of the market maker indeed increases the market price of liquidity. Moreover, we find evidence for a destabilizing reinforcement between funding liquidity risks of a market maker and the realized bid/ask spread in the money market as theoretical models such as Gromb and Vayanos (2002) would suggest.

[Table 6 about here]

An additional interesting finding of Model 9 is that an increase in the bank's perceived credit risk led market participants to not only require a significantly higher risk premium from the market maker when borrowing to him, but the market maker himself also significantly increased the rate he charged for his loan issues to the market, although he couldn't completely roll over his increased idiosyncratic credit risk. This suggests banks borrowing from the market maker not only paid 'their' credit risk premium, but they also had to pay for the lender's increased credit risk premium. Hence, the credit risk premia actually seem to have accumulated along the 'intermediation chain' in the interbank market which might have contributed to the extreme increase in the spread between secured and unsecured interbank rates observed after the collapse of Lehman Brothers.

7 Robustness checks

In addition to our nine main models, we estimate further models to check the robustness of our results. All robustness checks are carried out for Model 8.

The first robustness check accounts only for those banks that had a stable AA credit rating over the whole sample period and for which we observe at least one trade in the normal, subprime, and Lehman collapse time phase (25 banks in total with 29% of the transactions being loans). This allows us to check whether our results stay robust if we drop those counterparts from the regression, where the bank might have closed its credit lines and where our results may suffer from a selection bias. As it can be seen, although LIQ and Maturity become insignificant, their interaction term is highly significant. Hence, our results stay robust. *RC 2* depicts the results when we use the volume-weighted LIQ measure which gives a higher weight to larger-sized transactions in the normalization of the average maturity: As it can be seen, our results stay robust and the volume-weighted funding liquidity risk measure is highly significantly positive. The same holds when we re-run model 8 with the Euribor instead of the Eurepo in *RC 3*.

Turning to *RC 4*, where we substituted the five-year Bloomberg implied credit risk spread with the one-year default probability of the market maker to account for the rather shorter-term nature of money market transaction, we find that our results also remain the same. Next, we split our sample in a tranquil time period from January 2007 to August 2007 (Model 5a) and a crisis time period (Model 5b): Again, we find that the results for our key variables remain robust, although we note that for the crisis part of our sample, the market maker actively manages its funding liquidity risk level instead of purely reacting to it. Moreover, it seems that the relationship effect only holds for loans for the crisis period and that the market maker's credit risk did not play a role in the pricing of transactions in the pre-crisis phase.[16] In *RC 5c*, we account for a structural break in the LIQ time series: Most prominently, looking at Figure 1(b), one might get the notion that *LIQ* has undergone a regime shift after the middle of October 2007. Running the regression between the 21^{st} October 2007 and the end of our sample period reveals that our results stay broadly robust.

The results of *RC 6* where we run a apnel regression with trader fixed effects point towards the same overall direction as our plain OLS regressions. Hence, controlling for time invariant unobservable trader effects leave our results largely intact.

Finally, *RC 7* uses both the *Fixed rate* and the *Eurepo* in their natural levels instead of their natural log. Also here, we do not find a major difference to the results of our main models.

[Table 7 about here]

We run various additional robustness checks which are not reported here for brevity. Amongst others, we substituted the Eurepo with the marginal bid rate set exogenously by the European Central Bank to check whether our results may suffer from an endogeneity problem since the market maker is part of the Eurepo and Euribor panel. Our results stay robust with the exception of the *3M unsecured-secured rate* which turned negative. Moreover, we experimented with various sensible specifications for the normalization of the mean maturity mismatch ($\bar{m}$): Amongst others we calculated (i) the average maturity $\bar{m}$ over the whole sample period, where we assume that the bank targets a certain mean-maturity mismatch over time, (ii) the rolling mean of the average outstanding maturity $\bar{m}$ at at time $t + i$, (iii) the average maturity $\bar{m}$ by excluding the upper 1% of the maturity distribution. The results stay robust to any of these specifications. Next, we interacted LIQ with a dummy variable for the introduction of fixed-rate full allotment tenders which the European Central Bank introduced on the 15^{th} October 2008. This was one of the key responses by the ECB in the aftermath of the Lehman collapse where banks could obtain an unlimited amount of liquidity at a fixed rate, provided they could pledge eligible collateral. We find that the positive effect of LIQ on the pricing of money market transactions remains also for the fixed-rate full allotment phase and that this effect is not mitigated by this central bank measure. We also interacted LIQ with a dummy variable for high

[16] Note that the credit risk of the market maker before August 2007 was pretty stable. Using a diff-in-diff regression to analyze the separate effect between loans and deposits, we continue to find an insignificant effect for either transaction type.

net money market funding (equaling 1 whenever NMMF was in its upper 20% percentile). Our results stay robust and we find for the interaction term that a larger net money market funding decreases the positive effect of a higher funding liquidity risk level, although the economic effect of this interaction term is negligible. Finally, we run our main specification with the largest 60 counterparts by traded volume only which would also not alter our findings.

8 Conclusions

All in all, our empirical analysis provides four key insights: First, the larger the funding liquidity risk assumed by the market maker, the higher the market price for liquidity (the price the market maker pays for deposits and the rate he charges for loans). The market maker seems to hoard liquidity in response to a higher liquidity risk exposure. Second, a higher accumulated liquidity risk by the marker maker goes along with a higher term premium (longer term loans and deposits pay a higher rate compared with respective shorter contracts). Thus it becomes pricier for other market participants to reduce their liquidity risk by trading with the market maker. Third, the market liquidity – measured by the realized bid-ask-spread charged by the market maker – rises significantly if the funding liquidity risk retained by the market maker increases. Thus, transaction costs in the unsecured money market increase and the efficiency of the liquidity reallocation within the banking sector deteriorates with the market makers' funding liquidity risks. Forth, market liquidity is more sensitive to the accumulated liquidity risk for longer-term contracts. The realized bid-ask-spread rises substantially for longer term loans and deposits if the market maker's liquidity risk increases, while such an increase has much less of an effect for short term contracts. This suggest that particularly in the term lending segment of the money market, liquidity and transactions costs depend on the market makers' funding liquidity risks. Furthermore, we find, at least in the crisis period, that a deterioration in the market makers own perceived credit quality not only required him to pay a higher risk premium on deposits received, but he also charged a higher mark-up on loans. Hence, he was apparently able to roll over his own elevated funding costs to his borrowers. In sum, we find along various dimensions a detrimental effect of the market makers' assumed funding risks and funding costs on the market conditions in the unsecured money market.

These findings have important policy implications. Obviously, the market maker is a money center bank and a systemically important financial institution for the Euro area. But it is not only systemically important because it imposes a huge credit risk on interbank lenders and thus creates a risk of significant knock-on effects. In fact, our results also show that liquidity becomes pricier and the efficiency of its reallocation in the banking system is impaired by higher retained funding liquidity risks of the market maker (and not only by a failure of this financial institution, which obviously becomes also more likely the higher the accumulated risks are). But if an elevated funding liquidity risk level of money center banks indeed affects money market liquidity, then liquidity risks are likely to feed back into an elevated risk associated with a given maturity mismatch, potentially sparking off a liquidity spiral very much in line with Shleifer and Vishny (1997), Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009). Thus, our results support the view that systemically important financial institutions should not only be subject to higher minimum capital requirements but that they should also be obliged to maintain a larger liquidity buffer.

As regards to monetary policy implications, our results indicate that funding risks of market makers in the Euro area money markets, in particular their retained liquidity risk, aggravated the increase in unsecured money market rates and contributed to the dry-up of this market. Thus, the European Central Bank was obviously well advised to mitigate these effects not only by allotting further liquidity to the banking system, but also by providing liquidity at longer maturities via LTRO operations. This way, the ECB likely helped to contain an even stronger increase in the spread levels between unsecured and secured interbank lending rates and fostered market liquidity in the unsecured interbank market.

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Table 1: Descriptive statistics

This table presents descriptive statistics for the explanatory variables for the time period January 2007 to December 2008. The **Fixed Rate**, **Amount**, and **Maturity** were directly supplied by the market maker, the **Liquidity risk & market funding** are calculated using the trading book data and the formulas outlined in the variable construction section, and the **Credit risk measures** were obtained from Bloomberg on a daily basis.

	Observations	25th percentile	Median	75th percentile	Minimum	Maximum	Standard Dev.
Main trade characteristics							
Fixed Rate (in %)	17,721	3.51	3.85	4.00	1.40	4.89	0.57
Fixed Rate (in logs)	17,721	1.26	1.35	1.39	0.34	1.59	0.19
Eurepo (in %)	17,721	3.72	4.01	4.06	1.87	4.52	0.47
Eurepo (in logs)	17,721	1.31	1.39	1.40	0.63	1.51	0.14
Euribor (in %)	17,721	3.73	4.02	4.13	2.23	5.39	0.46
Euribor (in logs)	17,719	1.32	1.39	1.42	0.80	1.69	0.13
Amount (in EUR millions)	17,721	2.75	9.70	43	0.0001	3000	265
Maturity (in days)	17,721	1.13	1.20	3.12	1.02	185	5.90
Liquidity risk & market funding							
LIQ (in EUR 100 billion)	17,720	-0.40	-0.15	-0.01	-2.22	0.27	0.43
NMMF (in EUR billion)	17,720	-5.34	-2.19	0.53	-31.56	14.21	5.13
LIQ Daily (in EUR 100 billion)	17,705	-0.36	-0.14	-0.01	-2.06	0.23	0.41
NMMF Daily (in EUR billion)	17,705	-5.06	-2.03	0.57	-29.00	14.21	4.96
LIQ volume-weighted (in EUR 100 billion)	17,720	-0.05	-0.02	0.01	-1.72	0.48	0.31
Credit risk measures							
Bloomberg Implied credit risk spread	17,721	–	–	–	–	–	–
Bloomberg 1-year default probability	17,721	–	–	–	–	–	–
3 months unsecured - secured rate (in %)	17,721	0.08	0.60	0.80	0.06	3.17	0.50

Table 2: Descriptive statistics according to rating and transaction type

This table depicts the total observations, the means of the three trading book entries, and the number of counterparties with respect to the rating and separated between deposit intakes and loan issuance for the time period January 2007 to December 2008. In total, there were 384 unique counterparts from which the bank obtained interbank deposits and 82 unique counterparts to which the bank issued interbank deposits. Note that the figures in this table account only for those observations for which at least one official credit rating was available (9,735 out of 17,721 observations had a credit rating).

		AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**
Total Observations	Deposit	31	2,065	1,397	961	1,881	1,190	38
	Loan	133	1,380	650	9			
Mean Fixed Rate (in %)	Deposit	3.42	3.63	3.63	3.50	3.63	3.67	3.92
	Loan	3.96	3.95	3.90	4.07			
Mean Maturity (in days)	Deposit	5.47	1.82	1.89	2.82	2.47	2.96	4.37
	Loan	1.85	1.85	1.83	1.81			
Mean Amount (in EUR millions)	Deposit	88	72	61	24	17	9	25
	Loan	954	592	428	27			
Number of Counterparties	Deposit	5	48	65	28	28	26	4
	Loan	2	36	33	1			

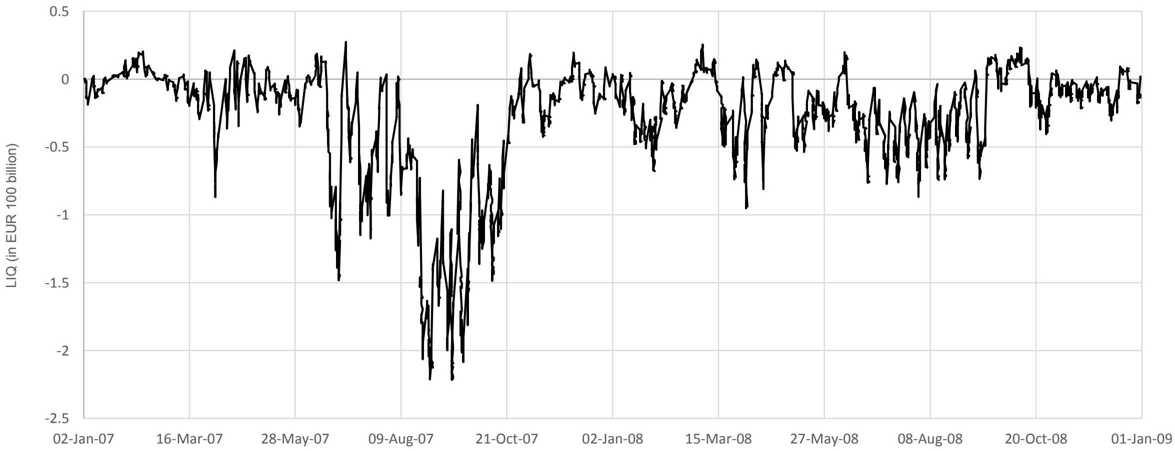
Table 3: Descriptive statistics over different time regimes

This table presents the descriptive statistics for key trading book metrics over (i) the total sample period, (ii) the tranquil phase from January 2007 to August 2007, (iii) the subprime crisis phase from August 2007 to September 2008, and (iv) the post Lehman collapse time period from September 2008 to December 2008. * Note that the **Mean Rating** is calculated as a simple mean, where 1=*AAA*, 2=*AA*, 3=*A*, 4=*BBB*, 5=*BB*, 6=*B* and 7=*CCC*.

	Total Sample 01/2007 - 12/2008	Tranquil Phase 01/2007-08/2007	Subprime Crisis 08/2007 - 09/2008	Lehman collapse 09/2008 - 12/2008
Mean Fixed Rate (in %)				
Deposits	3.61	3.70	3.93	2.80
Loans	3.93	3.84	4.04	3.10
Median Maturity (in days)				
Deposits	1.2	1.21	1.19	1.2
Loans	1.28	1.12	1.29	1.41
Median Amount (in EUR millions)				
Deposits	7	5.5	7	8.5
Loans	500	400	500	700
Mean Rating* (excluding non-rated)				
Deposits	3.84	3.74	3.88	3.86
Loans	2.25	2.21	2.26	2.25
Number of transactions				
Deposits	15,209	4,075	7,644	3,490
Loans	2,512	650	1,695	167
Number of counterparties				
Deposits		215	256	212
Loans		50	84	23
Average trades per day				
Deposits	32	27	28	47
Loans	8	7	10	3
Number of traders		23	29	18

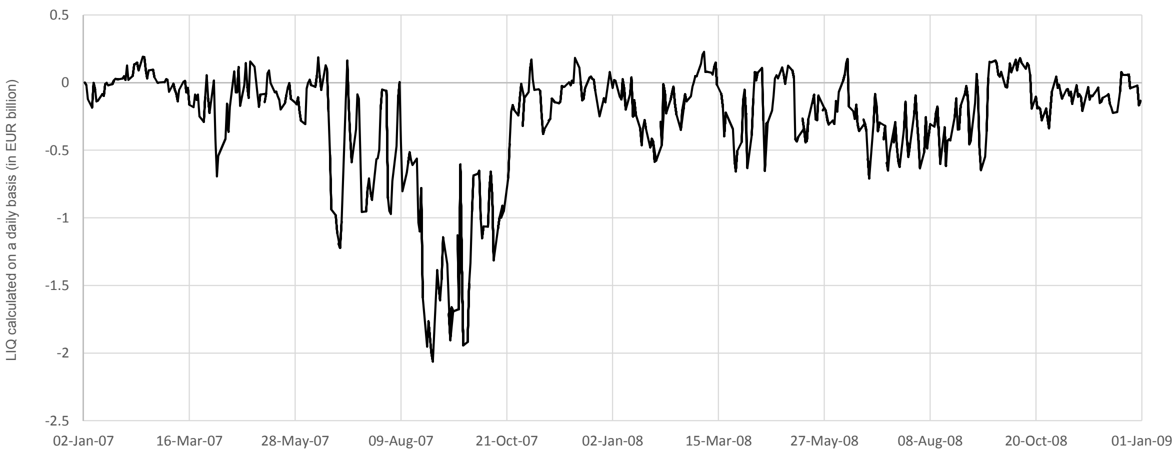
Figure 1: Evolution of the the funding liquidity risk over the sample period 2007 - 2008

The three graphs depict the evolution of three different specifications for the main explanatory variable, the **Funding liquidity risk** (LIQ): Sub-graph (a) depicts the evolution of LIQ where the maturities of loans and deposits are normalized with the equal-weighted average maturity across all currently outstanding loans and deposits. This specification of LIQ is used for the main models. Sub-graph (b) depicts the evolution of LIQ where the maturities of loans and deposits are normalized with the volume-weighted average maturity across all currently outstanding loans and deposits. Here, the maturity which is used to normalize the maturity of each loan or deposit is more heavily influenced (weighted) by larger-sized transactions. Finally, sub-graph (c) shows the end-of-day version of LIQ, where the maturities of loans and deposits are normalized with the equal-weighted average maturity across all currently outstanding loans and deposits. The latter two LIQ measures will be used in the robustness section.



(a) LIQ with the equal-weighted average maturity

(b) LIQ with the volume-weighted average maturity



(c) LIQ with the equal-weighted average maturity on a daily basis

Table 4: Main Models

This table reports the OLS estimates for the main model specifications for the full set of 17,721 observations (January 2007 to December 2008). The dependant variable, the agreed **Contractual Fixed Rate** of the transaction, is measured in logs. The regression output is separated by variable group attributes. The first variable group consists of the key *standard pricing factors*: **Eurepo** is the risk-free rate and measured in logs. The maturity of the Eurepo has been matched to the maturity of the respective transaction. The **Trade Type** is equal to 1 if the transaction is a loan issued by the market maker to another financial institution and 0 if the market maker obtained a deposit from another financial institution (base case). The **Amount** and the **Maturity** variables are measured in EUR millions and in days respectively. The *liquidity risk & market funding* group includes the **Funding liquidity risk** (LIQ) and the **Net money market funding** (NMMF) measures. Note that **LIQ** and **NMMF** are calculated on a trade-by-trade basis using all 17,721 transactions, except for the **Daily** version in Model 4(b) which use the previous day's end-of-day value. Both variables are lagged by one trade observation. The third variable group includes two *credit risk measures*: The **Bloomberg Implied credit risk spread** is the five-year implied credit default swap spread of the financial institution from which we obtained the data and supplied by Bloomberg (DRSK function) and lagged by one day. The **3M unsecured-secured interbank rate** is the spread (in %) of the three months Euribor to the three months Eurepo interbank rate, lagged by one day, and controls for increases in the aggregate credit risk in the money market. The **Relationship measures** are equal to 1 if the bank from which we obtained the data has traded with the same counterparty and in the same transaction type within the last 50 observations. The **Access to the MDF on same day** is a dummy variable equal to 1 for the whole day if the bank reverted at the end of the business day to the marginal deposit facility of the Eurosystem; the price effect is reported separately for deposit intakes and loan issuance. Note that the base group for the **Ratings** variables in Model 3(a) and 3(b) is the *AAA*-rated group. **Quarterly counterparty fixed effects** are constructed by interacting the Trade Type variable by the unique Bank identifiers on a quarterly basis. Both, the **Ratings** and the **Quarterly counterparty fixed effects** are interacted with the **Type** of transaction to account for a different pricing impact depending on whether the transaction is for a loan issuance or deposit intake. Also note that from Model 3(b) onwards, monthly time fixed effects have been included. Calculated standard errors are robust in the baseline models (Model 1 and 2) and cluster robust by Bank ID in all other models (Model 3 to 8). All models include a constant term which is omitted from the output.

Contractual Fixed Rate (in logs)	**Model 1** Baseline	**Model 2(a)** LIQ	**Model 2(b)** NMMF	**Model 2(c)** LIQ & NMMF	**Model 3(a)** Ratings	**Model 3(b)** Time FE	**Model 3(c)** CP FE	**Model 4(a)** LIQ x MAT	**Model 4(b)** Daily	**Model 5** CDS	**Model 6** CCR	**Model 7** REL	**Model 8** MDF
Main trade characteristics													
Eurepo (in logs)	1.21***	1.21***	1.21***	1.21***	1.21***	1.04***	1.05***	1.05***	1.06***	1.05***	1.05***	1.05***	1.06***
	(0.0037)	(0.0040)	(0.0039)	(0.0040)	(0.0075)	(0.019)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)	(0.016)
Trade Type (=1 if Loan)	0.047***	0.048***	0.047***	0.047***	0.034****	0.026	0.33***	0.33***	0.33***	0.33***	0.33***	0.33***	0.44***
	(0.0019)	(0.0018)	(0.0019)	(0.0019)	(0.023)	(0.023)	(0.0035)	(0.0035)	(0.0035)	(0.0033)	(0.0033)	(0.0032)	(0.029)
Amount (in EUR millions)	0.00000081	0.0000010	0.00000080	0.0000013	-0.000000063	0.0000020	0.0000031	0.0000031	0.0000028	0.0000033	0.0000034	0.0000032	0.0000031
	(0.0000020)	(0.0000020)	(0.0000020)	(0.0000020)	(0.0000070)	(0.0000060)	(0.0000031)	(0.0000032)	(0.0000031)	(0.0000031)	(0.0000031)	(0.0000032)	(0.0000031)
Maturity (in days)	0.0018***	0.0018***	0.0018***	0.0018***	0.0018***	0.0017***	0.0014***	0.0015***	0.0015***	0.0015***	0.0015***	0.0015***	0.0015***
	(0.00016)	(0.00016)	(0.00016)	(0.00016)	(0.00021)	(0.00019)	(0.00020)	(0.00023)	(0.00022)	(0.00024)	(0.00024)	(0.00024)	(0.00024)
Liquidity risk & market funding													
LIQ (in EUR 100 billion)		0.0026*		0.0063***	0.0062***	0.0044*	0.0071***	0.0064**		0.0046*	0.0081***	0.0081***	0.0082***
		(0.0013)		(0.0015)	(0.0021)	(0.0026)	(0.0025)	(0.0026)		(0.0026)	(0.0026)	(0.0026)	(0.0026)
NMMF (in EUR billion)			-0.00013	-0.00047***	-0.00045***	-0.00039**	-0.00079***	-0.00079***		-0.00062***	-0.00076***	-0.00074***	-0.00075***
			(0.00010)	(0.00011)	(0.00015)	(0.00017)	(0.00016)	(0.00016)		(0.00016)	(0.00016)	(0.00016)	(0.00016)
(LIQ x Maturity) Interaction								0.00026		0.00026	0.00027	0.00027	0.00027
								(0.00025)		(0.00025)	(0.00025)	(0.00025)	(0.00025)
LIQ Daily (in EUR 100 billion)									0.013***				
									(0.0028)				
NMMF Daily (in EUR billion)									-0.0014***				
									(0.00017)				
(LIQ Daily x Maturity) Interaction									0.00040*				
									(0.00021)				
Credit risk measures													
Bloomberg Implied credit risk spread										0.0016***	0.0013***	0.0013***	0.0013***
										(0.00019)	(0.00017)	(0.00016)	(0.00016)
3M unsecured-secured rate (in %)											0.020***	0.020***	0.021***
											(0.0036)	(0.0036)	(0.0037)
Relationships (same counterparty)													
Deposit (1 if deposit intake last 50 trades)												-0.0018*	-0.0016****
												(0.0010)	(0.0010)
Loan (1 if loan issued last 50 trades)												0.0041*	0.0044*
												(0.0023)	(0.0023)
Access to the MDF on same day													
Effect on the deposit price													0.024*
													(0.012)
Effect on the loan price													-0.088***
													(0.027)
Controls and summary statistics													
Official Credit Ratings (by Type)	No	No	No	No	Yes	Yes	No	No	No	No	No	No	No
Monthly time FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly Counterparty FE (by Type)	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,721	17,720	17,720	17,720	17,720	17,720	17,720	17,705	17,705	17,720	17,720	17,720	17,720
Degrees of freedom	4	5	5	6	17	40	1,828	1,829	1,829	1,830	1,831	1,833	1,835
Standard errors	Robust	Robust	Robust	Robust	Cluster R.	Cluster R.	Cluster R.	Cluster R.	Cluster R.	Cluster R.	Cluster R.	Cluster R.	Cluster R.
Adjusted R^2	0.89	0.89	0.89	0.89	0.89	0.92	0.95	0.95	0.95	0.95	0.95	0.95	0.95

Robust standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 5: The relative importance of the pricing factors

	Total Sample (M8)		*Normal Phase (RC5a)*		*Crisis Phase (RC5b)*	
	Shapley value	% of R2	Shapley value	% of R2	Shapley value	% of R2
Eurepo (in logs)	0.686	72.06%	0.446	53.17%	0.650	67.86%
Trade Type	0.012	1.30%	0.018	2.09%	0.013	1.31%
Amount (in EUR millions)	0.004	0.39%	0.008	0.95%	0.004	0.40%
Maturity (in days)	0.003	0.34%	0.005	0.59%	0.004	0.38%
LIQ (in EUR 100 billion)	0.018	1.92%	0.105	12.47%	0.012	1.21%
NMMF (in EUR billion)	0.008	0.81%	0.023	2.69%	0.008	0.80%
Bloomberg Implied CDS spread	0.042	4.38%	0.019	2.30%	0.045	4.74%
3M unsecured-secured rate (in %)	0.132	13.86%	0.024	2.88%	0.182	19.00%
Total explanatory value	**0.952**	**100.00%**	**0.839**	**100.00%**	**0.957**	**100.00%**

Table 6: The difference between the price of loans to deposits for varying levels of LIQ (Model 9)

To illustrate the role of liquidity spirals, a difference-in-difference approach is applied for model 8 is applied, where the **Trade Type** variable is interacted with all explanatory covariates in order to analyze the incremental pricing effect of a loan transaction above the price effect of a deposit trade (base case). Note that we substitute the Quarterly Counterparty FE with the Official Credit Ratings dummy (interacted by Type). x implies an interaction term and **Type** is equal to 1 if a loan is issued by the bank. The base effect of each interaction term is for a deposit trade. The estimation results are as follows (Obs = 17,720; Adjusted R^2 = 0.9062; degrees of freedom=49; * p<0.1, ** p<0.05, *** p<0.01; the results for the Rating dummies and the monthly time fixed effects are omitted):

log(Fixed rate) $=$ $0.24^{***}x$ (Type $=$ Loan) $+1.05^{***}$ x log(Eurepo) $-0.14^{***}x$ log(Eurepo)xType $+0.000014^{***}x$ Amount $-0.000016^{***}x$ Amount$x$Type $+0.0018^{***}x$ Maturity $-0.0014^{***}x$ Maturity$x$Type $-0.00055^{***}x$ NMMF $+0.00042x$ NMMFxType $+0.0013^{***}x$ Bloomberg Implied credit risk spread $-0.00034^{***}x$ Bloomberg Implied credit risk spread$x$Type $+0.012^{***}x$ 3M unsecured-secured rate $+0.064^{***}x$ 3M unsecured-secured rate$x$Type$+0.0053^{*}x$ LIQ $+0.0072^{*}x$ LIQxType $-0.11^{***}x$ Constant

The output shows that the regression line for loans slopes higher for every unit increase in **LIQ** than the line for deposits. However, the *price difference* between loans and deposits may or may not be significantly increasing over varying levels of the market maker's funding liquidity risk. This table depicts the loan-to-deposit price difference over the whole range of observed funding liquidity risk levels. Whenever the confidence interval does not include zero, the difference between the mark-up on a loan transaction compared to a deposit transaction in response to a rise in LIQ is considered statistically significant. A rising value of the price difference implies that the the gap between the deposit and loan price increases the higher the funding liquidity risk is and hence, implies a widening of the bid/ask spread. This table reports the price difference (price-Δ) between a loan and deposit transaction for the whole range of the funding liquidity risk measure (in Euro 100 billions) in increments of 0.25, including the 95% confidence interval. Note that * p<0.1, ** p<0.05, *** p<0.01.

Level of Funding Liquidity Risk in Euro 100 bn.	Price-Δ loans-to-deposits	95% Confidence interval for the price delta	
-2.20	0.026^{***}	0.013	0.039
-1.95	0.028^{***}	0.016	0.040
-1.70	0.030^{***}	0.019	0.040
-1.45	0.031^{***}	0.023	0.040
-1.20	0.033^{***}	0.026	0.040
-0.95	0.035^{***}	0.029	0.041
-0.70	0.037^{***}	0.032	0.042
-0.45	0.039^{***}	0.034	0.043
-0.20	0.040^{***}	0.035	0.046
0.05	0.042^{***}	0.036	0.048
0.30	0.044^{***}	0.037	0.051

Table 7: Robustness Checks

The dependant variable, the agreed **Contractual Fixed Rate** of the transaction, is measured in logs for RC 1 to 6 and in % for RC 7. The regression output is separated by variable group attributes. The first variable group consist of the key *standard pricing factors*: **Eurepo** is the risk-free rate and measured in logs (except in RC 7, where it is measured in %). The **Euribor** in RC 3 is the unsecured European interbank rate. The maturity of the Eurepo and Euribor has been matched to the maturity of the respective transaction. The **Trade Type** is equal to one if the transaction is a loan issued by the market maker to another financial institution and zero if the market maker obtained a deposit from another financial institution. The **Amount** and the **Maturity** variables are measured in EUR millions and in days respectively. The *liquidity risk & market funding* group includes the **Funding liquidity risk** (LIQ) and the **Net money market funding** (NMMF) measures. Note that **LIQ** and **NMMF** are calculated on a trade-by-trade basis using all 17,721 transactions. In addition, RC 2 and 5(c) use the **Volume-weighted funding liquidity risk** (LIQ-VOL) which weights each outstanding transaction by the volume of the transaction, relative to the current total outstanding volume across all deposits and loans. All three variables are lagged by one trade observation. The third variable group includes three *credit risk measures*: The **Bloomberg Implied credit risk spread** is the five-year implied credit default swap spread of the financial institution from which we obtained the data and supplied by Bloomberg (DRSK function) and lagged by one day. In RC 4, the one-year default probability of the market maker is used (**1-year PD**) as a measure of the market maker's credit risk. The time series is obtained from Bloomberg (DRSK function) and lagged by one day. The **3M unsecured-secured interbank rate** is the spread (in %) of the three months Euribor to the three months Eurepo interbank rate, lagged by one day, and controls for increases in the aggregate credit risk in the money market. The **Relationship measures** are equal to one if the bank from which we obtained the data has traded with the same counterparty and in the same transaction type within the last 50 observations. The **Access to the MDF on same day** is a dummy variable equal to 1 for the whole day if the bank reverted at the end of the business day to the marginal deposit facility of the Eurosystem; the price effect is reported separately for deposit intakes and loan issuance. **Quarterly counterparty fixed effects** are constructed by interacting the Trade Type variable by the unique Bank identifiers on a quarterly basis. Both, the **Ratings** and the **Quarterly counterparty fixed effects** are interacted with the **Type** of transaction to account for a different pricing impact depending on whether the transaction is for a loan issuance or deposit intake. All models include a constant term which is omitted from the output.

Fixed Rate (in logs) for RC 1-6	**RC 1**	**RC 2**	**RC 3**	**RC 4**	**RC 5(a)**	**RC 5(b)**	**RC 5(c)**	**RC 6**	**RC 7**
FixedRate (in %) for RC 7	Stable sample	LIQ-vol. weight	Euribor	1-year PD	Jan07 - Aug 07	Aug07 - Dec08	Date > 19Oct07	Trader FE (Panel)	Non-log
Eurepo (in logs)	1.06***	1.06***		1.08***	1.40***	1.04***	1.04***	1.06***	
	(0.056)	(0.016)		(0.015)	(0.051)	(0.015)	(0.015)	(0.0088)	
Euribor (in logs)			0.86***						
			(0.017)						
Eurepo (in %)									0.86***
									(0.018)
Trade Type (=1 if Loan)	0.36***	0.44***	0.40***	0.44***	0.0093	0.44***	0.0000015	0.042	1.27***
	(0.042)	(0.029)	(0.016)	(0.029)	(0.0065)	(0.029)	(0.0000046)	(1328.0)	(0.051)
Amount (in EUR millions)	0.000010	0.0000030	0.0000017	0.0000029	0.0000024	0.0000034	0.43***	0.0000024	0.000011
	(0.0000083)	(0.0000031)	(0.0000025)	(0.0000032)	(0.0000036)	(0.0000044)	(0.029)	(0.0000026)	(0.000012)
Maturity (in days)	0.00049	0.0014***	-0.0017***	0.0015***	0.00019	0.0020***	0.0018***	0.0016***	0.0051***
	(0.00084)	(0.00021)	(0.00058)	(0.00024)	(0.00026)	(0.00016)	(0.00017)	(0.00012)	(0.00086)
Liquidity risk & NMMF									
LIQ (in EUR 100 billion)	0.0051		0.0060**	0.012***	0.0092***	0.0043		0.0083***	0.022**
	(0.0081)		(0.0024)	(0.0026)	(0.0024)	(0.0038)		(0.0026)	(0.0092)
NMMF (in EUR billions)	-0.00087**	-0.00012	-0.00072***	-0.00088***	-0.00060***	-0.00070***	-0.0014***	-0.00073***	-0.0020***
	(0.00042)	(0.00011)	(0.00015)	(0.00016)	(0.00016)	(0.00021)	(0.00021)	(0.00016)	(0.00057)
LIQ x Maturity Interaction	0.0049**		0.0000025	0.00029	-0.00038	0.00085**		0.00017	0.00032
	(0.0020)		(0.00040)	(0.00025)	(0.00049)	(0.00034)		(0.00021)	(0.00072)
LIQ-VOL (in EUR 100 billion)		0.021***					0.038**		
		(0.0032)					(0.015)		
LIQ-VOL x Maturity Interaction		-0.00053					-0.0036		
		(0.00039)					(0.0023)		
Credit risk measures									
Bloomberg Implied CDS spread	0.00096***	0.0013***	0.0016***		0.00061	0.0014***	0.00078***	0.0012***	0.0031***
	(0.00020)	(0.00016)	(0.00022)		(0.00053)	(0.00016)	(0.00018)	(0.00013)	(0.00050)
1-year default probability				19.2***					
				(1.96)					
3M unsecured-secured rate (in %)	0.0079****	0.022***		0.024***	0.58***	0.026***	0.033***	0.021***	0.035***
	(0.0051)	(0.0037)		(0.0040)	(0.084)	(0.0041)	(0.0050)	(0.0026)	(0.0099)
Relationship (same counterparty)									
Deposit intake last 50 trades	0.0026	-0.0016	-0.0019	-0.0016	-0.0011	-0.0013	-0.0032**	-0.0017*	-0.0043
	(0.0029)	(0.0010)	(0.0012)	(0.0011)	(0.0019)	(0.0012)	(0.0012)	(0.00098)	(0.0034)
Loan issued last 50 trades	0.0068*	0.0044*	0.0039*	0.0049**	-0.00013	0.0053*	0.0023	0.0042**	0.016*
	(0.0038)	(0.0023)	(0.0021)	(0.0023)	(0.0020)	(0.0030)	(0.0025)	(0.0021)	(0.0086)
Access to the MDF on same day									
Effect on the deposit price		0.024*	0.019****	0.027**		0.023*	0.022*	0.024***	0.098***
		(0.012)	(0.012)	(0.013)		(0.012)	(0.012)	(0.0038)	(0.031)
Effect on the loan price		-0.088***	-0.10***	-0.085***		-0.088***	-0.088***	-0.089***	-0.21***
		(0.027)	(0.014)	(0.028)		(0.027)	(0.027)	(0.020)	(0.046)
Controls									
Monthly time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly Counterparty FE (by Type)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Summary statistics									
Observations	2,429	17,720	17,718	17,720	4,724	12,996	11,191	17,720	17,720
Degrees of freedom	413	1,836	1,835	1,836	593	1,343	1,142	1,862	1,836
Standard errors	Cluster R.	Cluster R.	Cluster R.	Cluster R.	Cluster R.	Cluster R.	Cluster R.	Conv.	Cluster R.
Adjusted R^2	0.93	0.95	0.95	0.95	0.82	0.95	0.96	0.94	0.93

Robust standard errors in parentheses

* $p<0.1$, ** $p<0.05$, *** $p<0.01$