Kiel

Working Papers

Kiel Institute
for the World Economy

Euro Money Market Trading During Times of Crisis

by Falko Fecht and Stefan Reitz

No. 2012 | November 2015

Web: www.ifw-kiel.de

Kiel Institute for the World Economy, Kiellinie 66, 24105 Kiel, Germany

Kiel Working Paper No. 2012 | November 2015

Euro Money Market Trading During Times of Crisis

by Falko Fecht und Stefan Reitz

Abstract:

This paper uses the order book for 2007 and 2008 of a key Euro area market maker in the unsecured money market to estimate a stylized pricing model which explicitly accounts for the over--the--counter structure and the unsecured nature of these transactions. The empirical results suggest that the market maker learns from order flow to update her beliefs about the fundamental value of the overnight rate, but this information aggregation via order flow was increasingly hampered as the crisis unfolded. In addition, order size was also used to infer the unobservable component of a counterparty's credit risk.

Keywords: G15; E43; C32

JEL classification: Euro money market; financial crisis; market microstructure; pricing behavior

Falko Fecht
Frankfurt School of Finance
60314 Frankfurt, Germany
E-mail: f.fecht@fs.de

Stefan Reitz
Kiel Institute for the World Economy
24106 Kiel, Germany
E-mail: stefan.reitz@ifw-kiel.de

Euro Money Market Trading During Times of Crisis*

Falko Fecht† Stefan Reitz‡

October 9, 2015

Abstract

This paper uses the order book for 2007 and 2008 of a key Euro area market maker in the unsecured money market to estimate a stylized pricing model which explicitly accounts for the over–the–counter structure and the unsecured nature of these transactions. The empirical results suggest that the market maker learns from order flow to update her beliefs about the fundamental value of the overnight rate, but this information aggregation via order flow was increasingly hampered as the crisis unfolded. In addition, order size was also used to infer the unobservable component of a counterparty's credit risk.

JEL Classification: G15; E43; C32
Keywords: Euro money market; financial crisis; market microstructure; pricing behavior

*Corresponding author: Stefan Reitz. Kiel Institute for the World Economy, Kiellinie 66, D-24105 Kiel , Germany, email: stefan.reitz(a)ifw-kiel.de, phone: (+49) 431 8814 284. We thank participants to the European Economic Association Meeting in Toulouse, the Infiniti Conference in Prato, the German Economic Association Meeting in Hamburg, the Bundesbank/SAFE conference on Supervising banks in complex financial systems and various university research seminars for helpful comments.

†Frankfurt School of Finance, Frankfurt, Germany.

‡University of Kiel and Kiel Institute for the World Economy, Kiel, Germany.

1 Introduction

The recent financial crises highlighted the pivotal role of a proper functioning money market for both monetary policy as well as financial stability. Disruptions in the money market impaired the reallocation of liquidity in the banking sector and thereby impeded banks' mutual liquidity risk sharing, leading to bank runs and contagious spillovers to the broader financial system. At the same time severe money market tensions rendered traditional monetary policy instruments ineffective, calling for unconventional policy interventions. It is therefore of utmost importance to thoroughly understand the functioning and in particular the malfunctioning of this market. In contrast to the previous literature in this paper we take explicitly the decentralized over-the-counter (OTC) structure of this market into account and use a microstructure approach to analyze the pricing of a key market maker.

The existing literature on prevailing frictions in unsecured money markets so far focused on counterparty credit risks, accompanying informational asymmetries and resulting liquidity hoarding, while maintaining the assumption of a centralized, competitive market.[1] However, Ashcraft and Duffie (2007) point out the importance of considering the decentralized nature of this market and the relevance of search frictions. In such a market setting revelation and aggregation of private information and thus learning about the fundamental value of an asset is complex and depends on the trading structures.[2]

Duffie et al. (2005) show that this particular property of OTC markets gives rise to a market-maker structure of the trading process in order to mitigate search costs and facilitate trade.[3] Given that intermediaries play a key role in such a market with uncertainty about the fundamental value of the traded asset, a market microstructure approach can also be used to model the learning of the market maker

[1] See Flannery (1996), Afonso, Kovner Schoar (2011), Freixas Jorge (2008), Abbassi et al. (2015), Allen Carletti Gale (2009), Acharya Merrouche (2013).

[2] See, for instance, Duffie at al (2007).

[3] See also Babus and Kondor (2013) for a further theoretical model of this relationship.

and his trading and pricing of interbank claims.[4]

In this paper we follow this idea and use a market microstructure model that explicitly takes uncertainty and the market maker's learning about the fundamental value of liquidity into account.[5] Several papers argue that the value of liquidity might be determined by the distribution of excess reserves in the banking sector and the fear of squeezes.[6] Since the distribution of banks' excess reserves is not observable, the market value of unsecured interbank liquidity is also unknown. Thus, in contrast to previous studies, we analyze the recent money market disruptions taking the effect of uncertainty and learning about the fundamental value of liquidity on pricing and trading of interbank claims into account.

In particular, we adapt the empirical market microstructure model of Madhavan and Smidt (1991) to the specificities of the unsecured money market. In general, this model is constructed to reveal the extent to which market makers learn about the fundamental value of a traded asset from incoming orders. In case of the money market, particularly during times of crisis, the market maker's learning clearly will also relate to the unobservable component of counterparties' credit risk. To identify this learning process we control for observable counterparty credit risk information and maturity spreads. This approach enables the derivation of a single pricing equation for liquidity offered and obtained by the market maker taking his learning from incoming orders about the fundamental price of liquidity explicitly into account. We estimate the pricing equation and determine market makers' inference about the value of liquidity and how it is incorporated into bid- and ask-prices for

[4]Craig and von Peter (2010) provide evidence of tiering in the German interbank market and show that the money center bank serve as intermediaries or market makers. Afonso and Lagos (2015) show that intermediation matters for pricing and access to liquidity in the Federal Funds market.

[5]Note we use the term fundamental value of liquidity in order to distinguish it from a bank's private value of liquidity that is also determined, for instance, by its credit risk premium, its collateral holdings, and its investment opportunities. We define the fundamental value as the price for overnight liquidity that would emerge in a Walrasian market allowing for heterogenous counterparty credit risk, uncertainty about it, and liquidity hoarding.

[6]See, for example, Acharya et al. (2012) and Fecht et al. (2011). Also the fundamental value of liquidity varies depending on whether high or low credit risk banks are demanding reserves.

interbank liquidity.

For that purpose we obtained a data set that comprises the tick-by-tick trading record of a key market maker of the Euro area's interbank market from the beginning of 2007 to the end of 2008. Empirical studies of the money market are in general scarce, because data of this market is scanned due to its OTC structure. But even the data used so far in other papers such as data from the EONIA panel, transaction data from the eMID trading platform or data derived from payment systems are insufficient for our purpose, because they do not allow to derive a precise and comprehensive picture for all trades of a market maker. Data covering the EONIA panel capture only transactions of large banks on one side of the market. Thus they do not allow to study the role of an intermediary. The e-MID data suffer from a severe bias during the crisis as most international banks withdrew from this platform. Additionally the most comprehensive data sets derived from payment systems usually lack small foreign banks, as they often do not participate in payment systems. Further, the time stamp derived with the Furfine (1999) approach for the deal is not precise: payments corresponding to loans might be delayed–at least within a day. This also affects the precision of the sequencing of trades that is essential for a market microstructure analysis. Thus only the comprehensive and precise trading book information reported in our data set allows us to study how the market maker responds to the sequence of orders.

The estimation of the pricing equation provides several interesting insights. First, the market maker indeed seems to update her belief about the fundamental value based on the order flow she observes in tranquil times. Controlling for a large variety of other covariates such as the trade size as well as the trade direction (buy or sell) are important determinants of the market maker's pricing of liquidity. This confirms the view that in a decentralized market equilibrium prices are determined by the sequencing of orders obtained by the market makers as put forward, e.g., by

Afonso and Lagos (2015). Strikingly, this information aggregation via order flow was increasingly hampered as the crisis unfolded. Second, the market maker also draws on the customer bank's order size to infer private information about its current level of credit risk. This is also in line with Bräuning and Fecht (2015) and Abbassi et al. (2015), who argue that banks obtain private information about their counterparts through past trades in the interbank market. Third, our results suggest that in the course of the crisis half spreads increased substantially and inventory considerations became important.

The remainder of the paper is organized as follows. In the next section we briefly review the related literature. In Section 3, we develop a microstructural model of the dealer's trading in the unsecured segment of the Euro money market. Section 4 provides a detailed description of the data. In section 5, we estimate the model and discuss the empirical results. A final section concludes this paper.

2 Literature Overview

Our analysis draws on many different strands of the vast literature on money market functioning and malfunctioning. A variety of different approaches stresses market imperfections in a Walrasian market context. Furfine (2001), Flannery and Sorescu (1996), and Bruche and Suarez (2010) stress that elevated counterparty credit risk can lead to spreads which freeze the market. Based on interbank loan data extracted from the Fedwire payment system Afonso et al. (2011) find evidence for these market frictions. Flannery (1996), Freixas and Jorge (2008), and Heider, Hoerova, and Holthausen (2009) argue that asymmetric information about counterparty credit risk leads to a lemons problem in the interbank market, eventually generating a market dry-up. Using interbank loans extracted from the Euro area payment system TARGET2, Abbassi et al (2015) find evidence for private information in money markets. Rochet and Tirole (1996) show in this context that private information and peer monitoring plays an important role in overcoming the adverse selection problem. Cocco et al. (2009) and Bräuning and Fecht (2015) show that established lending relationships help mitigate informational asymmetries about counterparty credit risk. Our work contributes to this literature as it shows that banks do indeed try to infer information about counterparties' credit risk from bilateral trades.

Allen, Carletti, and Gale (2009) and Caballero and Krishnamurthy (2008) emphasize the importance of liquidity hoarding in times of interbank market failures. In these models, banks are not willing to lend even to high-quality counterparties because they prefer to keep liquidity for precautionary reasons. Similarly, in Diamond and Rajan (2011) and Acharya et al. (2012) banks hoard liquidity expecting high returns when competitor banks in need of cash are forced to sell at fire sale prices. Acharya and Merrouche (2013) find evidence for liquidity hoarding in the UK money market. Indirect evidence for precautionary hoarding in the Euro money market is also provided by Eisenschmidt and Tapking (2009), showing that the increase in Euribor rates cannot be fully explained by counterparty risk measures alone. Similarly, Kuo et al. (2010) document a significant shortening of the maturities at which interbank liquidity has been offered in the 2007/2008 financial crisis. In sum all these approaches indicate that even in a Walrasian market the distribution of liquidity across different banks matters for the market price of liquidity: If banks with higher credit risk, banks that are more opaque, banks with worse future access to the interbank market and banks with less market power are predominantly short in liquidity then the equilibrium market price for liquidity will be higher.

Following Ashcraft and Duffie (2007), a more recent strand of the literature on money markets emphasizes the OTC structure of unsecured money markets and stresses their decentralized, search-driven nature. Several papers such as Duffie et al (2005) and Babus and Kondor (2013) study pricing of assets traded in OTC markets with heterogenous information about the assets' fundamental value. They also allow for an endogenous emergence of market makers. For the interbank money market only Afonso and Lagos (2015) explicitly account for liquidity intermediation of dealer banks. All those papers generally show that given heterogenous characteristics of banks, some contributions indeed endogenously assume the role of a market maker in the interbank market. Craig and von Peter (2010) provide evidence of a tiering structure in the German interbank market whereby core banks serve as intermediaries for peripheral banks. We build on those approaches as we assume that the trader from which we obtained the order book data serves as a money market maker. Furthermore, following this literature we acknowledge that the fundamental value of liquidity (i.e. the equilibrium price of central bank reserves that would prevail in a Walrasian market) is unobservable and the market maker tries to infer it from the order flow he receives. In doing so we build on the standard market microstructure literature such as Kyle (1985) , Glosten and Milgrom (1985), Glosten (1989) and in particular on Madhavan and Smidt (1991) in bringing our analysis to the data.

3 Modeling the Euro Interbank Market

In this section we follow - and subsequently extend - the model of Madhavan and Smidt (1991) to analyze the market makers' trading behavior in the Euro money market. The Bayesian model of intraday specialist pricing originally explains security price movements against the backdrop of asymmetric information, inventory holding costs and trade execution costs. The Madhavan and Smidt (1991) model is based on an opaque market structure because the market maker cannot condition his quotes on market-wide order flow or quotes from his competitors. This OTC property particularly applies to the unsecured segment of the Euro money market as it is decentralized and intransparent. The interbank market for liquidity is decentralized as market participants are generally separated from one another and transactions take place through media such as telephone or computer networks.

Similar to other OTC markets, trading is performed in a decentralized fashion giving rise to market fragmentation and low transparency. The Euro money market is fragmented in the sense that trading activity in Euro area economies follows different institutional traditions and transactions may (and do) occur simultaneously or nearly simultaneously in the market at different prices (Hartmann et al., 2001). It lacks transparency because the absence of a physical marketplace makes the process of price-information interaction difficult to observe and understand (Duffie et al., 2005, 2007). Within this market environment, two types of participants can generally be distinguished: dealer banks (or market makers) and customer banks. While customer banks' trading behavior is derived mainly from their liquidity needs, dealer banks can be thought of as exchange-designated specialists who stand ready to provide liquidity to other market participants.[7]

In the following it is assumed that a market maker is approached by a customer bank asking for quotes at which the former is willing to lend or deposit funds. The full-information price of overnight liquidity to a particular customer, denoted by υ_t, is supposed to follow a martingale process containing two sources of relevant information. The first component is the fundamental value of liquidity, i.e the interest rate that would be charged for overnight reserves in a Walrasian market at the given distribution of excess reserves across banks of different type (credit risk, opacity, and incentive to hoard). The second component considers the idiosyncratic counterparty risk. It reflects the credit risk spread charged from the respective counterpart based on the publicly available data, such as his credit rating. Of course, both components should heighten dealers' concerns in times of money market tension.[8] The fact that the full-information price is partly unobservable gives rise

[7] In Ho and Saunders (1985) banks only differ by an idiosyncratic reserve shock and equilibrium money market rates are based on Walrasian auctioneering. Afonso and Lagos (2015) consider a money market where banks randomly meet counterparties to bargain on an overnight loan. The agreed interest rates depend on the banks' relative market power, but do not reflect the observed market maker structure.

[8] This setup is in line with Michaud and Upper (2008) stressing the role of bank-specific indicators such as default and funding liquidity risk as well as market indicators such as uncertainty

to adverse selection costs as the customer bank may hold private information.

Besides adverse selection costs, prices also deviate from expected values due to inventory considerations, group-specific credit risks, and maturity premia. Regarding inventory considerations, market microstructure research has shown that inventory carrying costs cause the market maker to adopt a pricing policy that depends on the current level of his inventory I_t. Intuitively, a market maker who has accumulated excess liquidity tries to attract lending orders by lowering the interest rate. In the typical inventory control model, prices are linearly related to the market maker's current deviation from the desired inventory I_t^*.[9]

Maturity effects result form the fact that the market maker provides liquidity over different horizons and quotes prices accordingly. For example, if the customer bank asks for a six month loan the pricing will be geared to the six month EURIBOR. Consequently, we construct a maturity spread variable M_t as the difference between the EURIBOR of adequate maturity and the EONIA at the day on which the trade occurs. Group-specific credit risk is publicly available information that arises from the credit rating of customer banks. The related risk premium is denoted by C_t and varies over time in accordance with changing default risk of the respective rating class or market risk appetite.[10] When additionally considering execution costs, the interest rate the market maker quotes to the customer bank is

$$p_t = \mu_t - \gamma(I_t - I_t^*) + \delta M_t + \rho C_t + \psi D_t, \tag{1}$$

where p_t denotes the market maker's quoted price, and μ_t is the market maker's expectation about the true level of the counterparty-specific overnight interest rate conditional upon his information set at time t. The variable $D_t \in \{-1, 1\}$ is an indicator variable, where $D_t = 1$ represents a lending transaction and vice versa,

about the path of expected overnight rates and the ease of executing a trade.

[9] Linear decision rules turned out to be optimal in a number of theoretical inventory models.

[10] In section 4 we provide a detailed description how exactly this credit spread variable is derived.

and ψ measures execution costs.

The customer bank's pre-trade expectation of the true value of its idiosyncratic overnight interest rate z_t is a weighted average of the public information price and a private signal w_t, and

$$z_t = \theta w_t + (1 - \theta) y_t, \tag{2}$$

where the coefficient θ depends on the precision of the information sources. In the standard Madhavan and Smidt (1991) model the variable w_t is a privately observed unbiased estimator of the stock price. Here, the private signal of the customer bank carries information about both the dynamics of market-wide excess liquidity or idiosyncratic information of the customer bank, such as deviations of its creditworthiness from published credit ratings or future liquidity shortages.[11] The customer bank's order flow q_t results from the perceived mispricing of the market maker and an idiosyncratic liquidity shock completely unrelated to the interest rate, x_t:

$$q_t = \alpha(z_t + \delta M_t + \rho C_t - p_t) + x_t, \tag{3}$$

where α is a positive constant. Following Glosten and Milgrom (1985) and Kyle (1985), the market maker considers the fact that the order flow depends on a private signal. In addition, adverse selection costs are supposed to vary positively with order size, since larger trades are associated with larger deviations of the private signal from the public information price (Easley and O'Hara, 1987; Glosten, 1989). In order to quote prices that are regret-free after the trade has occurred, the market maker has to infer the customer bank's private signal conveyed by the order flow. Bayesian updating gives a posterior mean μ_t of the true value of the idiosyncratic overnight interest rate

[11] Note that even the customer bank cannot fully capture its own creditworthiness as it also depends on current and future conditions on money and asset markets implying that w_t reflects only a signal of the full information interest rate.

$$\mu_t = \pi y_t + (1-\pi)(p_t - \delta M_t - \rho C_t + \frac{1}{\alpha} q_t), \tag{4}$$

consisting of a weighted average of the public signal and the inferred private signal from the order flow. The parameter $\pi \epsilon (0,1)$ is the weight placed on prior beliefs and depends on the relative precisions of the signals. Substituting equation (4) into equation (1) yields the price the market maker quotes to the customer bank:

$$p_t = \pi y_t + (1-\pi)(p_t - \delta M_t - \rho C_t + \frac{1}{\alpha} q_t) - \gamma(I_t - I_t^*) + \delta M_t + \rho C_t + \psi D_t, \tag{5}$$

which can be regarded as a public information price for a specific counterparty class corrected for adverse selection costs, inventory holding costs, maturity spread, and trade execution costs. Intense competition on interbank markets will prevent prices from deviating too far from the derived p_t. Otherwise, we should (permanently) observe quoted prices below trading costs on the part of the quoting agent or systematically inferior prices on the part of the customer bank cutting into its profits of regular businesses.

Equation (5) cannot be estimated directly because the public information price y_t is an unobservable variable. The Madhavan and Smidt (1991) solution to this problem is to approximate the pre-trade expectation about the true value of the idiosyncratic overnight interest rate using the last observed price adjusted for inventory effects, execution costs, as well as group-specific credit spread and maturity spread:

$$y_t = p_{t-1} + \gamma(I_{t-1} - I^*) - \delta M_{t-1} - \rho C_{t-1} - \psi D_{t-1} + \eta_t, \tag{6}$$

where η_t is the difference between the posterior mean at time $t-1$ and prior mean at time t, and incorporates a public news signal about the risk-free overnight rate and the idiosyncratic risk component of the counterparty. The resulting equation to be estimated is:

$$\Delta p_t = (\tfrac{1}{\pi} - 1)\gamma I^* + \tfrac{(1-\pi)}{\alpha\pi} q_t + \delta \Delta M_t + \rho \Delta C_t - \tfrac{\gamma}{\pi} I_t + \gamma I_{t-1} + \tfrac{\psi}{\pi} D_t - \psi D_{t-1} + \eta_t, \tag{7}$$

where Δp_t is the change in the interest rate between two incoming trades. The coefficients of the change of the maturity spread δ and the change of the credit spread ρ are generally expected to be estimated in the neighborhood of one. Depending on the exact construction of the variables, however, deviations from one may be observed. Equation 7 is over-identified as there are more coefficient estimates than parameters, which allows for testing the following theoretically-motivated restrictions.[12] Since the dealer is assumed to manage existing inventories by shading prices, coefficients should satisfy $-\frac{\gamma}{\pi} < 0 < \gamma$. Moreover, the model of anonymous liquidity trading predicts an asymmetric information effect on prices ($\frac{(1-\pi)}{\alpha\pi} > 0$), because the market maker rationally infers the customer bank's private signal about the true value of the idiosyncratic overnight rate from deal size. More importantly, the structure of the model expects the binary variable coefficients to satisfy $-\psi < 0 < \frac{\psi}{\pi}$ and $\frac{\psi}{\pi} > |\psi|$, the difference between the absolute values of the coefficients increasing in line with the perceived information content of the deal flow.[13] Thus, a Wald-type test may inform whether or not the market maker indeed uses order flow to infer information about the true value of the interest rate.

4 The Data

Our analysis is based on the trading book of one of the key players in the unsecured segment of the Euro money market. Trades typically originate from the Euro area and are arranged by the global headquarter of the bank. However, we also observe a significant amount of transactions with banks from Eastern Europe, the Middle

[12] Alternatively, we could apply maximum likelihood techniques thereby restricting the estimating with the theoretical priors.

[13] For details see Madhavan and Smidt (1991).

East, and the United States (Eastern Coast). Overall, there seems to be no preferred region in which the market maker trades. On average, three traders of the bank transacted trades with a given counterparty. For counterparties with which the market maker transacted frequently, up to eight traders were involved in trading activities. Hence, customer banks were not served by a single designated trader, but instead, each trader could trade with any counterpart. Over the sample period 2007/2008, the market maker had a stable high-grade credit rating ensuring that the empirical results on money market trading are not *a priori* biased due to customer banks' concerns about the dealer's credit risk. A natural question is whether flows observed by the market maker are generally representative of market-wide liquidity demands in the Euro area. First, our market maker is among the largest dealers in the Euro money market contributing to the EONIA panel. The panel of banks currently consists of 36 banks with the highest volume of business in the Euro zone money markets. Second, this panel of most important dealers is perceived to account for a major market share and all of these large dealers have access to essentially the same set of large customers. Thus, money market trading within this environment is very competitive, implying that the data is likely to provide detailed insights into Euro money market liquidity trading.

The money market trading data investigated here contains tick-by-tick transactions from the unsecured market segment over a sample period from January 2nd, 2007 to December 31st, 2008, for a total of 510 trading days. Each trade record contains the following information: (1) date and time stamp of the trade, (2) trade direction, (3) transaction price, (4) maturity, (5) deal size, (6) clear name of the trader, (7) clear name of the customer bank, and (8) a central bank flag.

We only consider incoming trades (in Billions of Euro) initiated by customer banks for which our dealer will always be the supplier of or demander for liquidity. Outgoing trades would have been initiated by requesting quotes from other dealers or by submitting market orders to brokers and are executed at prices set by other dealers. A small number of transactions were with central banks, whereby the market maker participated in the weekly main refinancing operations and accessed the marginal deposit facility of the Eurosystem. We drop these observations since the price is set 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. Consistent with existing literature, order flow variables are calculated from the perspective of the deal initiator implying that customer banks' borrowing orders have a positive sign, and deposit orders have a negative sign. All overnight changes are removed from the sample so that all price effects are solely related to intraday order flow transacted by the dealer. Thus, from the overall 17,888 transactions a set of 17,378 intraday price changes remain to estimate the pricing equation.

Each counterparty has a unique customer code classifying trades according to their origin. This enables us to employ a number of important counterparty-specific control variables such as credit rating, frequency of trades, or average deal size of the given customer bank. This contrasts with nearly all of the available empirical work, where data is confined to either reported (indicative) quotes or, as is the case for the e-MID studies, counterparties of transactions remain anonymous until the settlement of trades.

Within the observation period from January 2007 and December 2008 two potential structural breaks were typically recognized. First, the financial crisis was perceived to unfold in the aftermath of BNP Paribas' announcement to shut down three US mortgage funds on August 9th, 2007. We take this event as the starting point of heightened concerns about counterparty risk and potential liquidity shortages in the money market. Second, the main financial crisis incident, however, was seen in the breakdown of Lehman Brothers on September 15th, 2008, also triggering the ECB's switch to a policy of fixed-rate tenders with full allotment. As a result we split up the data into three sub-samples, the first sub-sample ranging from January 2nd, 2007 to August 8th, 2007 (First), the second sub-sample running from August 9th, 2007 to September 12th, 2008 (Second), and the final sub-sample covering the period from September 15th, 2008 to December 31th, 2008 (Third). The following Table 1 presents the distribution of trades across sub-samples and maturities.

[Table 1 about here]

The upper part of Table 1 already reveals common practice in interbank trading, where market makers accumulate a large number of smaller deposits and lend higher amounts to a few borrowers. This standard feature is somewhat strengthened in the last sub-sample. When looking at the volumes of deposits and loans across maturities we generally find that the bulk of trading occurs within maturities up to seven business days with a strong emphasis on overnight transactions. The deposits per day halved when moving from the first to the second sub-sample and then strongly increased in the third period. This gives rise to the presumption that the role of precautionary hoarding may have changed during the crisis. Strikingly, the loan figures suggest that lending operations (per day) did not significantly decline in the second sub-sample and, in contrast to the public perception of the money market functioning, only went down by 34% in the aftermath of the Lehman default. This strongly confirms Afonso et al.'s (2011) notion that money markets were stressed, but not frozen.[14]

[Table 2 about here]

Table 2 presents the composition of the bank's trading by counterparty rating (upper part) and time of the day (lower part). While deposits are collected from

[14]The structure of the data is in line with the results of the ECB Money Market Survey 2009. Available under: http://www.ecb.int/stats/money/mmss/html/index.en.html

banks with a broad range of ratings, lending is typically confined to investment-grade banks. Particularly for a number of small private and non-EU banks ratings were not available and are classified in this way. Fortunately, this lack of data is of minor importance for loans, the sort of transactions where counterparty rating is especially important for money market pricing. Combining the differing number of trades across counterparty ratings with the trading volume data from Table 1 we can conclude that, in general, our market maker accumulated deposits from a large variety of counterparties and provided loans to a small number of investment-graded banks. The lower part of Table 2 reveals the typical U-shaped activity pattern over the average trading day. This is particularly pronounced for loan transactions but less in case of deposit transactions. In case of deposits the number of transactions in the morning session is generally lower than in later sessions, which might be due to the fact that customer banks shy away from handing out liquidity too early. This trading pattern is stable over different sub-samples, pointing to a fundamental property of banks' liquidity management.

The empirical estimation includes the variables of the above stylized model as well as a number of control variables helping to identify the trading behavior of the market maker. In the following, we discuss the construction of the dealer's inventory, the credit risk premium, the maturity premium, the time-of-the-day dummy, a relationship measure, an information revealing order flow variable, and the time series properties of the interest rate change.

The calculation of the bank's liquidity position involves the aggregation of all transactions across different market segments. Since the data set analyzed herein consists of unsecured transactions only, the resulting inventory time series does not show common properties like strong mean reversion because these features refer to the bank's overall inventory position. Nevertheless, in line with common standards in risk management, money market traders at the bank were facing strict position limits, especially in non-trading (overnight) hours. Given that these position limits restrict each trading desk, it is reasonable to assume that the traders' inventory in the unsecured market segment coincides with the bank's desired levels at the end of each trading day. Thus, we follow standard practice in empirical market microstructure and set the inventory (Billions of Euro) equal to zero at the beginning of a given trading day.

To control for a publicly observable credit risk premium in the dealer's lending operations we first obtain ratings of different agencies for each counterparty from Bloomberg. We then use the related Merill Lynch European corporate bond return (seven to ten years maturity) and subtract the Merill Lynch index return for European government bonds (seven to ten years maturity), each derived from the trading day of the transaction (Bloomberg). This implies that even in case of triple A counterparties we observe a (small) credit risk premium. The credit risk premium is set to zero in case no rating is available. We also consider the dealer's credit risk premium in deposit transactions as counterparty banks may have increasingly been concerned about the dealer's default probability as the financial crisis unfolded. The maturity premium considers the fact that a fraction of trades exceed overnight maturity. In these cases we subtract the related EURIBOR rates from EONIA, again derived from the trading day of the transaction.[15] Both credit risks and maturity spreads are in basis points (hundredth of a percent).

Empirical studies of financial markets repeatedly reveal time-varying trading activity throughout a trading day. Trading activity is supposed to be high in the morning hours, when market participants adjust to new (overnight) information. Around lunch time less trading occurs when dealers are away from their desks, before trading volume again increases in the afternoon session. Admati and Pfleiderer (1988) provide a model of U-shaped trading volumes, where informed traders are dealing with uninformed liquidity traders who are either discretionary as regards the

[15]EURIBOR and EONIA rates are taken from the ECB

time they are trading in the course of the day or non-discretionary in this respect. In this model, high-volume periods are obtained when (i) informed traders are attracted by the presence of many uninformed traders, so informed flows can easily be camouflaged and (ii) discretionary liquidity traders attend because of relatively low trading costs amid increased price competition due to high trading-activity. However, subsequent empirical contributions challenged the view that trading costs are low when informed agents trade in the market. Bollerslev and Domowitz (1993) argue that the U-shaped pattern in trading volume largely stems from non-discretionary liquidity trading that is most pronounced at the beginning and the end of the trading day. The time-varying nature of market conditions may in fact influence the pricing of the market maker. Thus, we construct three dummy variables to identify the morning session (8.00am. to 11.00am.), the lunch time session (11.00am to 3.00pm), and the afternoon session (3.00pm to 6.00pm).

An interesting property of OTC markets concerns the fact that market participants maintain strong business relationships among each other, thereby acquiring important counterparty information. For instance, Cocco et al. (2009) find that banks with a larger reserve imbalance are more likely to borrow funds from banks with whom they have a relationship, and to pay a lower interest rate than otherwise. We employ the number of trades with a given customer bank (NoT) until August 9th, 2007, to reveal potential pricing effects stemming from the history of the particular business relationship (in hundreds of trades). We interact this variable with a buying and selling dummy to allow for a differing influence on deposits and loans.

In empirical contributions to market microstructure, deal size is at the heart of the analysis as it potentially reflects the aggregation of private information. As outlined in the theoretical model of money market dealing, however, liquidity trading may interfere with informed orders. Assuming that liquidity trading prevails in smaller, regular sized orders we expect the information content of trades with deal size below their median to be negligible. Moreover, fixed cost degression in the trading process may further distort the estimation results because an increased deal size will come with a discount, thereby exerting a negative influence on the deal price. Under these circumstances only above-average deal sizes will provoke a market maker's price reaction as a result of asymmetric information. To calculate an information revealing variable we only maintain deal sizes exceeding the bank-specific median, while lower-than-median values are set to zero ($ExMed$). This variable is assumed to identify transactions, which are suitable to signal the urgency of liquidity demand beyond public available rating information or reflect more market-wide dynamics, if the counterparty is another major player in the market.

Finally, first differences of the reported transaction price (agreed interest rate) in basis points are taken as the dependent variable. Since the change of the interest rate exhibits strong negative intraday autocorrelation the econometric model also contains eight lags (statistically significant).[16] To control for the influence of monetary policy on the price-setting behavior we also introduce the change of the EONIA (in basis points).

5 Estimation Results

Equation (7) is estimated using Hansen's (1982) generalized method of moments (GMM). The estimated standard errors are adjusted for heteroscedasticity and serial correlation with the Newey-West (1987) covariance matrix correction. The set of instruments equals the set of regressors implying that the parameter values parallel OLS estimates, but do not rely on a specific error distribution (Bjønnes and Rime, 2005). In the first subsection we present the estimation results of the baseline model. In the second subsection the estimation equation additionally accounts for time-of-the-day effects and the influence of the deal size, respectively. Besides the full-sample

[16]The estimated autocorrelation coefficients are not reported in the tables, but are available on request from the authors.

estimation both models were re-evaluated using the three sub-sample periods.

5.1 Estimation Results of the Baseline Model

The GMM regressions generally exhibit R^2s of roughly 50%, reflecting a reasonable fit of the model in an intraday data environment. Regarding the control variables the following results are worth mentioning. Considering the different maturities of the transactions the market maker significantly adjusts prices to control for EURIBOR/EONIA spreads. In off-crisis times, for instance, the difference between the maturity-consistent EURIBOR rate and EONIA is fully covered by the transaction price as indicated by a parameter estimate (ΔMat) of 0.94. The maturity coverage is substantially diminished thereafter, when less than half of the EURIBOR/EONIA spreads were incorporated into prices by the market maker.[17] It might be argued that in the course of the crisis only a small number of dealer banks perceived to be safe enough for depositing liquidity remained in the market. This argumentation also applies for quote adjustments to policy rate changes. While the dealer quickly adjusts quotes in tranquil trading periods there is a significantly slower transmission of policy action to money market rates in times of crisis.

[Table 3 about here]

The relationship premium measured by the number of transactions with a given counterparty is small but significantly positive in both loans and deposits. This implies that customer banks pay a premium for frequent borrowing while earning a smaller premium for frequent lending. Interestingly, the importance of the relationship measure declined in the third sub-sample when the crisis in the interbank market became more severe.

The deal size of the trade, if statistically significant, is adversely signed. This is in contrast to the basic microstructure perception that order flow aggregates pri-

[17]Since the bulk of transactions are lending operations of customer banks the estimation results were mostly driven by deposit conditions. See Table 1 and 2.

vate information into market prices. As outlined in the data section, however, deal sizes also serve as an integral component of the market maker's pricing policy.[18] For instance, in the first sub-sample customer banks were charged roughly five basis points less for each billion euro deal size, while in the third sub-sample this figure rises to fourteen basis points. The fixed cost component measured by the lagged direction indicator variable rises substantially over subsequent samples. While we observe a tiny one basis point half spread before the start of the crisis, the spread nearly quadrupled in the second period and was fourteen times larger in the third period. These estimates are in line with indicative bid/ask spreads from a survey conducted among European-based dealers and brokers of roughly three, eight, and forty basis points for the respective periods and reflect the increasing tensions in the market. However, its overall moderate size points to a remarkable resilience of money market trading.

As outlined in the theoretical part of the paper a significant difference between the coefficients of the indicator variable and the lagged indicator variable reveals the market maker's perception whether or not order flow contains useful information. By dividing the parameter estimates of these regressors we can calculate the weight placed on prior beliefs. In the first estimation period this ratio is $\pi = 0.20$ implying an 80% weight put on order flow information. Starting from August 2007, the coefficient π becomes larger and approaches near-one values in the last sample indicating little room for order flow information. Obviously, the process of information aggregation is systematically hampered in times of crisis.

Regarding the inventory variable the regression results suggest little evidence for price shading in a well-functioning money market. Borderline significant parameter

[18]In a non-anonymous trading environment market makers focus on information about their counterparties and do not solely rely on the size of the trade. In addition, the customer bank would observe the impact of deal size on quoted prices and, most likely, split up trades accordingly (Huang and Stoll, 1997).

estimates in the first sub-sample lead to the conclusion that building up a positive or negative liquidity position is a minor concern of the market maker in normal times. The dealer seems to adjust quotes to encourage inventory-diminishing trades with customer banks in the second sub-sample, but the magnitude of the coefficient remains small.

When moving towards regressors reflecting counterparty-specific information we find the following interesting results. The variable $ExMed$, measuring the deal size in excess of its median, has been introduced as a proxy for private information of the trade initiator. Consistently signed and statistically significant coefficients suggest that the occurrence of large deal sizes indicates that counterparty banks have little opportunity to split up trades across a number of market makers. As expected, the impact becomes considerably stronger in the third sub-sample. The counterparty credit rating of customer banks ($\Delta Credit\ buy$) as a publicly available information component influences half spreads as theory suggests. Lower credit ratings (higher CDS spreads) generally lead to higher half spreads to be paid by customer banks. This impact is moderately larger in the third sub-sample than in the first one due to the fact that credit spreads themselves increasingly contained substantial liquidity premia. The credit rating of the dealer ($\Delta Credit\ sell$) exerts a significant influence on half spreads in the second and third sub-sample, but is insignificant in the first. This is in line with the perception that deposits with large market makers are safe in off-crisis trading regimes.

5.2 Robustness checks

In this subsection we test whether the above empirical results remain robust when additionally accounting for time-of-the-day and deal size effects. The potential role for time-of-the-day effects arises from theoretical and empirical studies revealing a time-varying trading activity throughout a trading day. Trading volume is high in the morning when traders adjust their portfolios to new information. Only little trading occurs around lunch time when dealers are away from their desks, and again trading activity increases in the afternoon session when market participants close unwanted open positions. In Admati and Pfleiderer (1988) the U-shaped trading volume feeds back to the trading behavior of market participants. In their setup informed traders are dealing with uninformed liquidity traders, who are either discretionary or non-discretionary with respect to the daytime trades are submitted. High trading volume is observed when (i) informed traders are attracted by the presence of a large number of uninformed traders, so that informed transactions can easily be camouflaged and (ii) discretionary liquidity traders attend because of relatively low trading costs amid increased price competition due to high trading-activity.[19] Moreover, Afonso and Lagos (2015) show that a bank's negotiation leverage depends on the overall distribution of excess balances, but decreases towards the end of the trading session when the chances to execute a desired trade diminish substantially. As a result, half spreads of the market maker should increase during the trading day. Thus, the time of the day may influence the pricing behavior of our dealer.

[Table 4 about here]

The estimation results reported in Table 4 suggest that the main results from the baseline model also apply here as well. Regarding the various control variables like the maturity premium, the monetary policy rate, and lagged price changes, parameter estimates are insignificantly different from the above values. The proxy variable for relationship banking remains positive for all specification and sub-samples again indicating a slightly higher interest rate for both frequent lenders and borrowers. The estimated coefficient of the inventory variable also shows very little variation across the trading day. Only in the third sub-sample do we find an increased tendency of the market maker to divert flows away from his order book. When interacting with

[19]However, Bollerslev and Domowitz (1993) argue that the U-shaped pattern in trading volume largely stems from non-discretionary liquidity trading that is most pronounced at the beginning and the end of the trading day.

the information revealing variable $ExMed$ with the time-of-the-day dummies we again only find the expected results in the third sub-sample. After the Lehman default the deal-size premia reflect the fact that the urgency to trade seems to be high in the morning when customer banks adjust to new overnight information and the end of the trading day when customer banks try to adjust to desired overnight positions.[20] Differentiating estimates of the trade direction indicator coefficients with respect to the time of day is informative in the sense that half-spreads are strictly increasing during the trading day (and exhibit the same sub-sample patterns as above). This is evidence in favor of Bollerslev and Domowitz (1993) expecting high non-discretionary liquidity trading at the end of the trading day and in favor of Afonso and Lagos (2015) stressing the importance of declining negotiation leverage of customer banks.

The following Table 5 contains regression results from a specification that differentiates between small, medium, and large trades. This is a standard procedure in empirical market microstructure to control for deal size effects, which may otherwise bias parameter estimates. Small trades are defined as transactions with deal size below ten million Euro, medium trades are transactions between ten million and 100 million Euro deal size, and large trades are above 100 million deal size.[21]

[Table 5 about here]

The estimation results on the control variables are comparable to the baseline specification. Again, the coefficient of the relationship variable is positive in all specifications and smaller in deposit transactions. The discount for increasing deal

[20]The introduction of time-of-the-day dummies seems to slightly interfere with deal size effects in the second sub-sample. In this intermediate period the $ExMed$ variable is statistically insignificant while the deal size exhibits a positive sign.

[21]We followed the suggestions of the bankers who provided the data. Of course, a different set of thresholds might be considered to control for deal size effects. Extensive experimentation, however, reveals overall robustness of results.

size is largely confined to the third sub-sample and is of similar magnitude as in the baseline model. Inventory effects on price changes are often statistically insignificant and small. A substantial price-shading effect is only observable for small trades in the third estimation period where, in case of a market maker's excess liquidity, deposits were discouraged by a seven points reduction of the interest rate. Finally, the adjustment of prices to control for maturity considerations is robust across deal size. As before, the maturity coverage is substantially diminished after the start of the crisis, when less than half of the EURIBOR/EONIA premium is contained in the market maker's trades.

Little variation across deal size of parameter estimates of lagged direction regressors capturing the fixed trading cost component generally confirms the usefulness of the deal size categorization. Although we observe a substantial increase of half spreads over different sub-samples, the fixed-cost deviations of small and large trades from medium trades are statistically insignificant for the second, third, and full sample period. Only small trades in off-crisis times were charged somewhat higher. When calculating the ratio for the parameter estimates of the direction and lagged direction indicator we find the weight placed on prior beliefs to be $\pi = 0.26$ for small trades, $\pi = 0.16$ for medium trades, and $\pi = 0.08$ for large trades in the period before the crisis. In line with market microstructure theory, the market maker relies more heavily on order flow information when deal sizes increase. In crisis periods, however, the usefulness of order flow information declines dramatically.

When moving towards counterparty-related variables the results confirm the findings of the previous specification. In case of medium trades, the group-specific counterparty credit risk premium dips in the second sub-sample before becoming quite important thereafter. Small trades were substantially charged for credit risk only in the period after the Lehman default, while quotes for large trades contain a significant risk premium only in regular trading environments. These results reflect the fact that in this sub-sample lending operations are largely confined to top-rated counterparties enjoying a similar creditworthiness as our dealer.

6 Conclusion

In this paper we propose an over-the-counter money market pricing model to investigate the trading behavior of a major dealer in times before and during the financial crisis. Our approach explicitly accounts for market microstructure issues of the trading process such as deal size, inventory considerations, counterparty risk, and relationship banking. To empirically estimate the model we use the order book of a major dealer containing all unsecured transactions with a cross-section of more than 400 customer banks in the Euro money market. Descriptive statistics reveal an increasingly unbalanced money market trading in the sense that funds from an increasing number of depositors were handed out to a decreasing number of borrowers. The empirical results of the market microstructure model suggest that in tranquil times the market maker indeed seems to update her belief about the fundamental value based on the order flow he observes. Controlling for a large variety of other covariates, both the trade size as well as the trade direction, are important determinants of the market maker's pricing of liquidity. This confirms the view that prices in a decentralized market equilibrium are determined by the sequencing of orders obtained by the market makers. However, order flow information is increasingly dismissed in times of crisis, implying that the process of information aggregation on the Euro money market is systematically hampered. Moreover, half spreads substantially increased and inventory considerations as well as counterparty default risk became more important. Against the backdrop of the size of the crisis, however, the Euro money market appeared to be surprisingly resilient.

References

Acharya, V. V, Gromb, D., and Yorulmazer, T., 2012, Imperfect Competition in the Interbank Market for Liquidity as a Rationale for Central Banking, *American Economic Journal: Macroeconomics*, 4(2), 184217.

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

Admati, A. and P. Pfleiderer, 1988, A Theory of Intraday Patterns: Volume and Price Variability. *Review of Financial Studies* 1, 3 – 40.

Afonso, G., A. Kovner, and A. Schoar, 2011, Stressed, Not Frozen: The Federal Funds Market in the Financial Crisis, *Journal of Finance* 66, 1109 – 1139.

Afonso, G., and R. Lagos, 2015, Trade Dynamics in the Market for Federal Funds, *Econometrica* 83(1), 263 – 313.

Allen, F., E. Carletti, and D. Gale, 2009, Interbank Market Liquidity and Central Bank Intervention, *Journal of Monetary Economics* 56, 639 – 652.

Allen, F., and D. Gale, 2000, "Financial Contagion", *Journal of Political Economy* 108(1). 1 – 33.

Babus, A., and p. Kondor, 2013, Trading and Information Diffusion in Over-the-Counter Markets, mimeo.

Bernhardt, D., and E. Hughson, 2002, Intraday Trade in Dealership Markets, *European Economic Review* 46, 1697 - 1732.

Bjønnes, G., and D. Rime, 2005, Dealer Behavior and Trading Systems in Foreign Exchange Markets, *Journal of Financial Economics* 75, 571 - 605.

Bollerslev, T., and I. Domowitz, 1993, Trading Patterns and Prices in the Interbank Foreign Exchange Market, *Journal of Finance* 48, 1421 – 43.

Bräuning, F., and F. Fecht, 2015, Relationship Lending in the Interbank Market and the Price of Liquidity, mimeo.

Bruche, M., and J. Suarez, 2010, Deposit Insurance and Money Market Freezes, *Journal of Monetary Economics* 57, 45 – 61.

Caballero, R., and A. Krishnamurthy, 2008, Collective Risk Management in a Flight to Quality Episode, *Journal of Finance* 63, 2195 – 2230.

Cocco, J., F. Gomes, and N. Martins, 2009, Lending Relationships in the Interbank Market, *Journal of Financial Intermendiation* 18, 24 – 48.

Craig, B., and G. von Peter, 2010, Interbank Tiering and Money Center Banks, BIS Working Papers No 322.

Diamond, D., and R. Rajan, 2011, Fear of Fire Sales, Illiquidity Seeking and the Credit Freeze, *The Quarterly Journal of Economics* 126(2), 557 – 591

Duffie, D., N. Garleanu, and L. H. Pedersen, 2005, Over-the-Counter Markets, *Econometrica* 73, 1815 – 1847.

Duffie, D., N. Garleanu, and L. H. Pedersen, 2007, Valuation in Over-the-Counter Markets, *Review of Financial Studies* 20, 1865 – 1900.

Easley, D., and M. O'Hara, 1987, Price, Trade Size, and Information in Securities Markets, *Journal of Financial Economics* 19, 69 - 90.

Easley, D., and M. O'Hara, 1992, Time and the Process of Security Price Adjustment, *Journal of Finance* 47, 577 – 605.

European Central Bank, 2009, Euro Money Market Survey, September 2009, http://www.ecb.int/pub/pdf/other/euromoneymarketsurvey200909en.pdf?3a4a738d6975f6aa02

Eisenschmidt, J. and J. Tapking, 2009, Liquidity Risk Premia in Unsecured Interbank Money Markets, ECB working paper No. 1024.

Fecht, F., H. Gruener, and P. Hartmann, 2012, Financial Integration, Specialization, and Systemic Risk, *Journal of International Economics* forthcoming.

Fecht, F., K.Nyborg, and J. Rocholl, 2011, The Price of Liquidity: The Effects of Market Conditions and Bank Characteristics, *Journal of Financial Economics*, 102(2), 344–362.

Flannery, M., 1996, Technology and Payments: Deja Vu All Over Again?, *Journal of Money, Credit and Banking* vol. 28(4), 965 – 70.

Flannery,M., and S. Sorescu, 1996, Evidence of Bank Market Discipline in Subordinated Debenture yields: 1983-1991, *Journal of Finance* 51, 1347 – 1377.

Freixas, X. and Jorge J., 2008, The Role of Interbank Markets in Monetary Policy: A Model with Rationing, *Journal of Money, Credit and Banking* 40, 1151 – 1176.

Freixas, X., B. Parigi, and J.-Ch. Rochet, 2000, Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank, *Journal of Money, Credit, and Banking* 32(3).

Furfine C., 1999, The Microstructure of the Federal Funds Market, *Financial Markets, Institutions, and Instruments*, 8(5), 24 – 44.

Furfine, C., 2001, Banks Monitoring Banks: Evidence from the Overnight Federal Funds Market, *Journal of Business* 74, 33 – 58.

Furfine, Craig, 2002, Interbank Markets in a Crisis, *European Economic Review* 46, 809 – 820.

Duffie, D., N. Garleanu, and L. H. Pedersen, 2007, Valuation in Over-the-Counter Markets, *Review of Financial Studies*, 20(6), 1865–1900

Glosten, L., 1989, Insider Trading, Liquidity, and the Role of the Monopolist Specialist, *Journal of Business* 62, 211 - 235.

Glosten, L., and P. Milgrom, 1985, Bid, Ask, and Transaction Prices in a Specialist Market With Heterogeneously Informed Agents, *Journal of Financial Economics* 14, 71 - 100.

Hartmann, P., M. Manna, and A. Manzanares, 2001, The Microstructure of the Euro Money Market, *Journal of International Money and Finance* 20, 895 – 948.

Hansch, O., N. Naik, and S. Viswanathan, 1999, Preferencing, Internalization, Best Execution, and Dealer Profits, *Journal of Finance* 54, 1799 - 1828.

Hansen, L., 1982, Large Sample Properties of Generalized Method of Moments Estimators, *Econometrica* 50, 1029 - 1054.

Heider, F., M. Hoerova and C. Holthausen, 2009, Liquidity Hoarding and Interbank Market Spreads: The Role of Counterparty Risk, Working Paper Series 1126, European Central Bank.

Huang, R., and H. Stoll, 1997, The Components of the Bid-Ask Spread: A General Approach, *Review of Financial Studies* 10, 995 – 1034.

Kuo, D., D. Skeie, and J. Vickery, 2010, How Well Did Libor Measure Bank Wholesale Funding Rates Furing the Crisis? Working paper, Federal Reserve Bank of New York.

Leitner, Y., 2005, Financial Networks: Contagion, Commitment, and Private Sector Bailouts, *Journal of Finance* 60(6).

Kyle, A., 1985, Continuous Auctions and Insider Trading, *Econometrica* 53, 1315 - 1335.

Madhavan, A. and S. Smidt, 1991, A Bayesian Model of Intraday Specialist Pricing, *Journal of Financial Economics* 30, 99 - 134.

Newey, W., and K. West, 1987, A Simple positive Semi-Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703 - 708.

Table 1: Descriptive statistics across maturity
510 trading days between Jan 2, 2007 – Dec 31, 2008

	First	Second	Third	Full sample
Trading days	154	280	76	510
sum	5594	8581	3713	17888
Deposit (%)	86.22	81.38	95.39	85.80
Loan (%)	13.78	18.62	4.61	14.20
Number of trades				
O/N	3800	5811	2564	12175
Up to 7 days	1610	2423	983	5016
8 to 30 days	134	268	136	538
31 to 60 days	30	59	23	112
61 to 90 days	10	6	5	21
91 to 180 days	9	12	2	23
Beyond 180 days	1	2	0	3
Sum	5594	8581	3713	17888
Loan (Bill. Euro)				
O/N	340.21	602.55	110.67	1053.43
Up to 7 days	78.31	231.08	22.73	332.12
8 to 30 days	0.00	0.00	8.27	8.27
31 to 60 days	1.04	0.00	0.00	1.04
61 to 90 days	0.00	0.00	0.00	0.00
91 to 180 days	0.08	0.00	0.00	0.08
Beyond 180 days	0.00	0.00	0.00	0.00
Sum	419.63	833.64	141.68	1394.95
Deposit (Bill. Euro)				
O/N	137.17	152.82	111.38	401.37
Up to 7 days	68.39	52.87	31.14	152.40
8 to 30 days	0.70	1.45	1.03	3.17
31 to 60 days	0.25	0.27	0.18	0.70
61 to 90 days	3.04	0.27	0.08	3.39
91 to 180 days	0.30	0.25	0.00	0.55
Beyond 180 days	0.00	0.00	0.00	0.00
Sum	209.85	207.92	143.81	561.58

Notes: Sub-sample periods are 'First': 01/02/07 – 08/08/07, 'Second': 08/09/07 – 09/12/08, and 'Third': 09/15/08 – 12/31/08.

Table 2: Descriptive Statistics Across Ratings and Day Time

510 trading days between Jan 2, 2007 – Dec 31, 2008

	First	Second	Third	Full sample
	Counterparty rating			
Number of loans				
AAA	69	178	72	319
AA	497	966	39	1502
A	129	410	59	598
BBB	12	22	1	35
BB	0	0	0	0
B	1	3	0	4
CCC	0	0	0	0
NR	63	19	0	82
Sum	771	1598	171	2540
Number of deposits				
AAA	123	83	73	279
AA	516	945	501	1962
A	686	708	485	1879
BBB	286	497	265	1048
BB	627	1022	340	1989
B	124	335	98	557
CCC	24	4	21	49
NR	2437	3389	1759	7583
Sum	4823	6983	3542	15348
	Day Time			
Number of Loans				
Morning	177	490	98	765
Noon	92	234	28	354
Afternoon	502	874	45	1421
Sum	771	1598	171	2540
Number of Deposits				
Morning	547	674	361	1582
Noon	1600	1851	1201	4652
Afternoon	2676	4458	1980	9114
Sum	4823	6983	3542	15348

Notes: Sub-sample periods are 'First': 01/02/07 – 08/08/07, 'Second': 08/09/07 – 09/12/08, and 'Third': 09/15/08 – 12/31/08.

Table 3: Money Market Spread Variation

510 trading days between January 2, 2007 – December 31, 2008 (17,378 obs.)

		First	Second	Third	Full Sample
NoT	buy	1.88 (0.27)***	3.03 (0.31)***	-0.31 (5.52)	2.76 (0.22)***
	sell	1.47 (0.12)***	0.66 (0.07)***	0.34 (0.12)***	0.76 (0.06)***
Deal Size		-4.75 (1.19)***	0.40 (1.21)	-14.24 (3.43)***	1.10 (0.94)
$ExMed$		4.88 (1.57)***	5.12 (1.78)***	17.61 (3.56)***	2.19 (1.31)*
Inventory		0.62 (0.22)***	1.36 (0.45)***	3.48 (2.21)	1.17 (0.34)***
Inventory(-1)		-0.37 (0.21)*	-1.11 (0.45)**	-3.26 (2.18)	-0.91 (0.34)***
Direction		6.24 (0.75)***	7.19 (0.55)***	19.13 (2.34)***	5.83 (0.38)***
Direction(-1)		-1.23 (0.61)**	-4.34 (0.46)***	-17.29 (2.27)***	-3.09 (0.34)***
ΔCredit	buy	0.06 (0.01)***	0.01 (0.00)***	0.09 (0.03)***	0.02 (0.00)***
	sell	0.01 (0.02)	0.01 (0.00)***	0.06 (0.02)***	0.00 (0.00)
ΔMat		0.94 (0.11)***	0.38 (0.02)***	0.38 (0.06)***	0.41 (0.03)***
EONIA(-1)		0.57 (0.09)***	0.19 (0.02)***	0.23 (0.04)***	0.23 (0.02)***
EONIA(-2)		0.32 (0.06)***	0.09 (0.01)***	0.10 (0.03)***	0.11 (0.01)***
R^2		0.49	0.48	0.51	0.46

Notes: The dependent variable is the change of the interest price measured in basis points between two incoming deals. The set of instruments equals the set of regressors implying that the parameter estimates parallel OLS estimates (Bjønnes and Rime, 2005). * (**, ***) denote significance at the 10% (5%, 1%) level. Sub-sample periods are 'First': 01/02/07 – 08/08/07,'Second': 08/09/07 – 09/12/08, and 'Third': 09/15/08 – 12/31/08.

Table 4: Spread Variation Across Day Time

510 trading days between January 2, 2007 – December 31, 2008 (17,378 obs.)

		First	Second	Third	Full Sample
NoT	buy	1.63 (0.28)***	2.85 (0.31)***	7.81 (6.17)	2.67 (0.22)***
	sell	1.56 (0.12)***	0.72 (0.08)***	0.31 (0.13)**	0.82 (0.06)***
Deal Size		-3.92 (1.24)***	3.20 (1.25)**	-9.84 (3.55)***	3.88 (0.99)***
$ExMed$	morning	6.70 (1.93)***	2.19 (2.91)	18.37 (4.22)***	-1.17 (1.75)
	noon	6.02 (2.37)**	2.26 (2.28)	10.71 (3.30)***	0.45 (1.73)
	aftern.	-0.17 (2.19)	-0.58 (2.12)	20.04 (5.49)***	-3.99 (1.66)**
Inventory	morning	0.55 (0.33)	2.06 (0.44)***	7.90 (2.23)***	2.02 (0.34)***
	noon	1.00 (0.33)***	1.70 (0.44)***	5.01 (2.07)**	1.73 (0.34)***
	aftern.	0.23 (0.39)	1.55 (0.49)***	4.63 (2.20)**	1.66 (0.38)***
Inventory(-1)	morning	-0.29 (0.24)	-1.28 (0.45)***	-2.56 (1.97)	-0.92 (0.35)***
	noon	-0.67 (0.33)**	-1.41 (0.47)***	-5.05 (2.03)**	-1.50 (0.36)***
	aftern.	-0.03 (0.39)	-1.35 (0.47)***	-4.85 (2.21)**	-1.45 (0.37)***
Direction	morning	3.30 (1.00)***	2.74 (0.89)***	13.72 (2.88)***	2.80 (0.64)***
	noon	5.30 (0.74)***	5.09 (0.57)***	19.77 (2.55)***	4.35 (0.47)***
	aftern.	8.35 (0.78)***	9.22 (0.56)***	21.00 (2.37)***	7.31 (0.40)***
Direction(-1)	morning	-0.87 (0.70)	-1.11 (0.62)*	-12.20 (2.52)***	-1.05 (0.48)**
	noon	-1.45 (0.63)**	-3.21 (0.47)***	-17.62 (2.49)***	-2.28 (0.42)***
	aftern.	-2.04 (0.65)***	-5.83 (0.49)***	-19.33 (2.37)***	-3.96 (0.36)***
ΔCredit	buy	0.05 (0.01)***	0.01 (0.00)**	0.09 (0.02)***	0.02 (0.00)***
	sell	0.01 (0.02)	0.01 (0.00)	0.06 (0.02)***	-0.01 (0.00)**
ΔMat		0.94 (0.11)***	0.37 (0.02)***	0.38 (0.06)***	0.40 (0.03)***
EONIA(-1)		0.58 (0.09)***	0.18 (0.02)***	0.25 (0.04)***	0.23 (0.02)***
EONIA(-2)		0.32 (0.06)***	0.08 (0.01)***	0.11 (0.03)***	0.11 (0.01)***
R^2		0.49	0.5	0.53	0.47

Notes: The dependent variable is the change of the interest price measured in basis points between two incoming deals. The set of instruments equals the set of regressors implying that the parameter estimates parallel OLS estimates (Bjønnes and Rime, 2005). * (**, ***) denote significance at the 10% (5%, 1%) level. Sub-sample periods are 'First': 01/02/07 – 08/08/07,'Second': 08/09/07 – 09/12/08, and 'Third': 09/15/08 – 12/31/08.

Table 5: Spread Variation Across Deal Size

510 trading days between January 2, 2007 – December 31, 2008 (17,378 obs.)

		First	Second	Third	Full Sample
NoT	buy	1.91 (0.28)***	2.54 (0.33)***	2.27 (5.21)	2.30 (0.24)***
NoT	sell	1.50 (0.12)***	0.62 (0.07)***	0.33 (0.13)***	0.71 (0.06)***
Deal Size		0.26 (1.16)	-0.29 (1.49)	-15.72 (6.57)**	1.91 (1.13)*
ExMed		1.27 (1.43)	5.63 (1.82)***	14.65 (3.78)***	1.43 (1.36)
Inventory	Small	0.44 (0.57)	0.06 (0.49)	7.36 (2.16)***	0.85 (0.64)
	Med	1.08 (0.41)***	1.62 (0.82)**	-1.66 (1.50)	1.26 (0.56)**
	Large	0.50 (0.25)**	1.60 (0.63)**	-0.11 (5.98)	1.47 (0.50)***
Inventory(-1)	Small	-0.32 (0.55)	0.31 (0.49)	-7.01 (2.16)***	-0.51 (0.63)
	Med	-0.79 (0.41)*	-1.14 (0.81)	1.84 (1.46)	-0.87 (0.54)
	Large	0.05 (0.22)	-1.74 (0.60)***	-0.35 (5.96)	-1.50 (0.48)***
Direction	Small	7.32 (0.84)***	6.66 (0.63)***	15.82 (2.63)***	5.55 (0.45)***
	Med	5.91 (0.81)***	7.36 (0.64)***	17.76 (2.77)***	5.75 (0.45)***
	Large	2.75 (0.79)***	7.50 (0.76)***	20.37 (2.65)***	5.35 (0.55)***
Direction(-1)	Small	-1.93 (0.71)***	-4.33 (0.55)***	-14.97 (2.59)***	-3.20 (0.40)***
	Med	-0.94 (0.72)	-4.48 (0.59)***	-15.14 (2.62)***	-2.96 (0.42)***
	Large	-0.21 (0.64)	-4.36 (0.59)***	-16.28 (2.35)***	-2.80 (0.41)***
ΔCredit buy	Small	0.02 (0.02)	0.02 (0.01)**	0.11 (0.04)**	0.05 (0.01)***
	Med	0.08 (0.02)***	0.03 (0.00)***	0.17 (0.03)***	0.04 (0.01)***
	Large	0.09 (0.01)***	0.00 (0.00)	0.04 (0.02)*	0.01 (0.00)***
ΔCredit sell	Small	0.00 (0.02)	0.02 (0.01)***	0.05 (0.02)**	0.00 (0.00)
	Med	-0.01 (0.03)	0.01 (0.01)**	0.04 (0.02)**	-0.01 (0.00)**
	Large	0.05 (0.04)	0.00 (0.01)	0.06 (0.03)**	-0.01 (0.01)
ΔMat	Small	0.96 (0.11)***	0.39 (0.02)***	0.37 (0.06)***	0.41 (0.03)***
	Med	0.97 (0.13)***	0.36 (0.02)***	0.38 (0.06)***	0.41 (0.03)***
	Large	0.79 (0.13)***	0.34 (0.03)***	0.40 (0.06)***	0.46 (0.03)***
EONIA(-1)		0.58 (0.09)***	0.19 (0.02)***	0.22 (0.04)***	0.23 (0.02)***
EONIA(-2)		0.32 (0.06)***	0.09 (0.01)***	0.10 (0.03)***	0.11 (0.01)***
R^2		0.49	0.49	0.52	0.46

Notes: The dependent variable is the change of the interest price measured in basis points between two incoming deals. The set of instruments equals the set of regressors implying that the parameter estimates parallel OLS estimates (Bjønnes and Rime, 2005). * (**, ***) denote significance at the 10% (5%, 1%) level. Sub-sample periods are 'First': 01/02/07 – 08/08/07,'Second': 08/09/07 – 09/12/08, and 'Third': 09/15/08 – 12/31/08.