THE RIMINI CENTRE FOR ECONOMIC ANALYSIS

WP 02_10

Paolo Zagaglia
University of Bologna
and The Rimini Centre for Economic Analysis, Italy

THE INFORMED TRADING IN THE EURO MONEY MARKET FOR TERM LENDING

Informed Trading in the Euro Money Market for Term Lending

Paolo Zagaglia*

First version: December 15, 2009
This version: February 3, 2010

Abstract

I address the role of information heterogeneity in the Euro interbank market for unsecured term lending. I use high-frequency quotes of bid and ask prices to estimate probabilities of informed trading for contract maturities from one month to one year. The dataset spans from November 2000 to March 2008, and includes the relevant events that characterize the developments of the Euro area money market. I obtain four main results. First, I show that the loose supply of liquidity of the ECB has not dampened the distortions arising from asymmetric information in the unsecured money market. I also find that the probability of trading with a better informed bank is higher on days when open market operations take place, and at the end of the maintenance period. This effect has strengthened during the turmoil. The results indicate that information is segmented, in the sense that heterogenous knowledge among banks is maturity-specific. Finally, the paper presents some evidence suggesting that the risk of trading with a counterparty that enjoys an enhanced information set is priced.

Keywords: Market microstructure, PIN model, money markets, term structure.
JEL classification: G14, E52.

*Sveriges Riksbank (Modelling Division), Università di Bologna (Dipartimento di Scienze Economiche) and Rimini Centre for Economic Analysis. E-mail: paolo.zagaglia@gmail.com. I am grateful to workshop participants at Università di Bologna and Stockholm University for their helpful comments, in particular Maria Elena Bontempi, Roberto Golinelli, Matthew Lindquist and Massimiliano Marzo. I owe a great debt of gratitude to Stefano Nardelli and Jukka Sihvonen for their continuous encouragement and insightful suggestions. Stefano Nardelli also generously provided the dataset used here. Julien Idier kindly explained the technical details of his work on the money market. Sanna Viskari provided excellent editorial assistance. The work for this paper started in 2008 during my visit to the Research Unit of the Bank of Finland. The financial support and warm hospitality of the Bank of Finland is gratefully acknowledged. The views expressed here are my own and should not be interpreted as reflecting the views of the Executive Board of Sveriges Riksbank. This research was carried out by the author for purely academic purposes and without financial support from any private institution.

1 Introduction

The interbank market for funds is an integral part of the short end of the term structure of interest rates. Banks lend to each other using different types of financial instruments typically with a maturity until twelve months. The peculiar aspect of this market is that the supply of liquidity to the banking system is fully controlled by the central bank. The characteristics of the operational framework depend largely on the central bank's strategy. In the Euro area, the implementation of monetary policy takes place through open market operations that aim to steer money market rates, thus affecting the entire term structure.

Since the functioning of the money market plays a role for the monetary transmission mechanism, the formation of prices in the interbank market of the Euro area has been subject of thorough investigation. A large number of contributions focus on the overnight segment.[1] In this part of the market, interest rate changes are typically driven by technical factors and idiosyncratic shocks to the short-term demand for funds that banks face. Thus, the supply of liquidity of the ECB has a determinant impact on overnight rates. The literature on volatility in the overnight segment focuses on the tensions arising between the management of daily liquidity conditions and the signals conveyed by the ECB about the monetary policy stance.[2] The transmission of volatility shocks across the term structure of the money market bears implications for the pricing of liquidity at maturities longer than the overnight.

In this paper, I investigate the role of asymmetric information among banks for the pricing of interbank deposits with maturity longer than the overnight. I consider a model of the microstructure of the money market where heterogeneity among market participants in the access to liquidity is a source for information asymmetries. In particular, the framework assumes that a fraction of banks find it harder to fulfill their liquidity needs. The remaining part of the banking system, instead, faces a more viable access to the supply of liquidity. Through enhanced trading opportunities, this latter set of banks can acquire more accurate information on the expected aggregate demand for liquidity, thus enjoying an information advantage.

The literature on market microstructure presents several models where trading patterns generate signals about the true unobserved value of financial assets. Easley and O'Hara (1992) build on the sequential trading model of Glosten and Milgrom (1987) to propose a measure of information heterogeneity in populations of traders, the so-called probability of

[1] A non-exhaustive list includes Angelini, Nobili and Picillo (2009), Baglioni and Monticini (2008), Beaupain and Durré (2008), Durré and Pilegaard (2003) and Heider and Hoerova (2009).

[2] In the jargon used in the official statements of the ECB, the liquidity supply should be 'neutral' (e.g., see ECB, 2005b). This means that the current stance of monetary policy should by driven only by the decision on the key interest rates. The management of the daily liquidity conditions should not generate deviations of market rates from the policy rate that can interfere with the monetary transmission mechanism in a systematic manner. As a result, interest-rate expectations at longer maturities should be decoupled from the evolution of the daily liquidity conditions. This also suggests that the provision of liquidity should be guided solely by the need to smooth out aggregate liquidity shocks. The neutrality of the liquidity policy is discussed in detail in Alonso and Blanco (2005), Cassola and Morana (2006, 2009), ECB (2005b, 2007), Durré and Nardelli (2008), Jardet and Le Fol (2007), and Zagaglia (2010).

informed trading (PIN). This framework suggests that the pattern of buy and sell orders unveils the sources of information heterogeneity in the market. Hence, the model of Easley and O'Hara (1992) emphasizes the role of institutional arrangements and market organization for the dissemination of knowledge and the determination of prices. The reason is that the institutional setup can affect the access to the channel of information transmission. For instance, Grammig et al. (2001) study the relation between asymmetric information and trading activity in the German stock market, and show that the PIN is higher in markets where trading is not anonymous.

The probability of informed trading has been used to study price formation in several markets. A recent application to the overnight segment of the Euro money market is provided by Idier and Nardelli (2008). The institutional framework of the money market requires banks to hold reserves over a given period of time, called the reserve maintenance period.[3] Since the overnight market allows banks to gather liquidity for very short-run needs, it is fair to assume that trading in this segment is initiated mainly for the purpose of complying with idiosyncratic liquidity shocks and reserve requirements. The ECB can impose sanctions on the banks that fail to comply with the reserve requirements. The presence of this threat also suggests that the banking system faces an 'inventory constraint' in the demand for liquidity. An additional key observation is that the ability to borrow from counterparties varies across banks. This happens because banks may lack the appropriate credibility or reputation to borrow in the interbank market, or because they may not have the assets needed to post collateral in collateralized borrowing contracts.

These features make the money market a natural field of application for the model of Easley and O'Hara (1992). Idier and Nardelli (2008) show that the ability of smaller banks to borrow in the overnight market has improved since 2004. They attribute this outcome to the incentives arising from the interaction between two changes in the practice of liquidity supply. These consist in the reform of the operational framework of the ECB in March 2004, and in the introduction of liquidity-absorbing operations at the end of each maintenance period in November 2004.

Differently from Idier and Nardelli (2008), I assume that the inventory constraints arise from funding obligations contracted by banks with maturities from one to twelve months. The time horizons for these liquidity needs depend on the strategies of asset-liability management that banks formulate in order to plan their cash flows. For instance, banks issue loans to their customers. The cash outflow at the beginning of the loan maturities generates a subsequent inflow of cash when loans are refunded by the customers. These funding flows correspond to different investment commitments. Furthermore, banks know they have to comply with the reserve requirements in future maintenance periods.

I use high-frequency quotes of bid and ask prices of term-lending contracts to estimate probabilities of informed trading. This dataset provides information on trading patters in

[3] A maintenance period lasts, on average, between 17 and 22 days.

over-the-counter segments where market reputation is a key consideration in the choice of a trading counterparty. As discussed earlier, the reputation factor creates heterogeneity in the banking system because it affects the ability of banks to borrow. Larger banks with solid balance sheets and diversified activities can engage more easily in bilateral trades. This also allows them to acquire information on the expected imbalance of liquidity, and provides the source for asymmetric information. The dataset spans from November 2000 to March 2008, and covers the main events that characterize the Euro area money market. In particular, in November 2005, the ECB introduced a policy of buoyant supply of liquidity in excess of the estimated benchmark demand of the system. The excess liquidity has been strengthened since the current financial turmoil hit the Euro area money market in August 2007.

The results show that information asymmetries have decreased across the money-market term structure after the reform of the operational framework of 2004. However, the probability of finding a trading counterparty with a better information has risen since the eruption of the turmoil in August 2007. This implies that larger banks with better market reputation have been capable of assessing the evolution of the aggregate liquidity conditions better than the rest of the banking system during the turmoil. The findings also indicate that there is information segmentation across the maturity structure. Different contract maturities are characterized by idiosyncratic information sets. On days when open market operations are carried out, and at the end of the maintenance period, banks obtain additional information. This pattern arises from the fact that the trading opportunities of informed banks increase. At the end of the maintenance period, the constraints of reserve requirements become binding. This enhances the demand for funds of the market. The liquidity operations of the ECB, instead, affect the ability of the participating institutions to relax the bottleneck of the demand for funds from the rest of the banking system. These effects have strengthened during the recent financial turmoil.

I also consider the effect of the policy of loose liquidity supply by the ECB. I show that this practice has worsened the market distortions arising from heterogenous knowledge. In other words, the abundant provision of liquidity has not removed the imbalances that give rise to the excess demand for term funding. This demand pressure can arise from the preference of lenders for contracts with shorter maturities. During times of uncertainty and large market volatility, this mechanism strengthens in segments where unsecured lending takes place. The reason is that counterparty risk becomes the key assessment factor for lending decisions. The recent experience of market turmoil has also been characterized by liquidity hoarding. This takes place because banks try to secure their funding needs against the possibility of market breakdown (e.g., see Heider, Hoerova and Holthausen, 2009). As a result, the supply of funds at longer maturities shrinks, and the demand for short-term liquidity is magnified.

The role of the PIN can be relevant also for understanding the transmission of monetary policy impulses from overnight to longer maturities. The expectations hypothesis of the term structure of interest rates is a cornerstone for the determination of long-term yields. Durré and

Pilegaard (2003) study the term structure of the Euro Overnight Interest Average (EONIA) swap rates and of the Euro Interbank Offered Rates (EURIBOR).[4] They find that deviations from the expectations hypothesis are typically small. By studying the microstructure of the market, this paper considers an alternative determinant of interbank rates. Following the literature on the stock and bond markets (e.g., see Easley, Hvidkjaer and O'Hara, 2002), I investigate the proposition that asymmetric information is a source of information risk in trading. Banks without information advantages face a positive probability of finding trading counterparties that enjoy a superior information set. Thus, uninformed banks face an information risk premium. I show that the probability of informed trading predicts both the bid-ask spread and the average rate at each maturity. This result holds both for in-sample and out-of-sample predictability. The PIN retains its forecasting ability also when other variables are included in the model, such as realized volatility. These findings suggest that information asymmetries could be priced in the money market.

This paper is organized as follows. Section 2 outlines the key characteristics of the money market that provide justification for the application of the model of Easley and O'Hara (1992). It also discusses how the model is adapted to the features of the money market. Section 3 describes the dataset and the method for classifying trades into buy or sell-initiated transactions. The results are discussed in Section 4. Section 5 presents some concluding remarks.

2 The model

2.1 Features of the Euro area money market

The framework employed in this paper departs from the observation that banks have asset-liability management strategies over different time spans. The need to put in place these plans generates a demand for liquidity with different maturities. These cash flows can arise from activities that follow systematic (planned) or non-systematic (unforeseen) patterns. One of the systematic sources of the demand for liquidity is related to the reserve requirements. Also, banks have investment plans or commitments whose financial flows can be partly known in advance.

The structure of the Euro area money market contemplates two sources of liquidity supply to the banking sector. The primary supply is operated by the ECB and takes place through three types of open market operations. Main refinancing operations (MROs) are weekly repurchase operations with a maturity of normally one week. They are executed as variable rate tenders with a minimum bid rate given by the policy rate. Longer-term refinancing operations (LTROs) are repurchase agreements with a monthly frequency and a maturity of

[4] EONIA and EURIBOR rates are daily average rates offered by a panel of representative banks selected by the European Banking Association. EURIBOR rates incorporate a credit risk premium. This is however not priced into EONIA swaps because these contracts do not involve an exchange of principals.

normally three months where the ECB is a rate-taker. Fine-tuning operations (FTOs) are executed on an ad-hoc basis through quick tenders or bilateral procedures. They take place generally at the end of reserve maintenance periods to resolve liquidity imbalances and to avoid further significant departures of the overnight rate from the minimum bid rate. Unlike the other two types of operations, FTOs can either supply or withdraw liquidity to the market depending on the sign of the imbalance.

As noted earlier, the ECB introduced several changes in its operational framework for monetary policy in March 2004. The aim of the reform was to maintain a low volatility of money market rates, in particular for the overnight segment. From a central bank's perspective, this issue is relevant because volatility spillovers from short to long maturities can interfere with the intended monetary policy stance, thus impairing the functioning of the transmission mechanism (see ECB, 2005a). The reform has changed the duration of the reserve maintenance period, and it has shortened the maturity of the main refinancing operations to one week.[5]

The liquidity provided by the ECB is distributed to the banking system through the interbank market. In this market, banks trade lending and borrowing contracts. These transactions can involve trades through bilateral direct deals, voice brokers and electronic trading platforms.[6] The market consists of four main segments, including the markets for secured and unsecured lending, for swap derivatives and short-term securities.[7]

2.2 The role of heterogeneity among market participants

The microstructure model considered in this paper postulates that heterogeneity among market participants in the access to liquidity is a source of asymmetric information. In particular, the framework assumes that a fraction of banks find it harder to fulfill their liquidity needs. The remaining part of the banking system faces a more viable access to the supply of liquidity. Through enhanced trading opportunities, this latter set of banks can acquire information on the expected liquidity imbalance and on the demand for funds, thus enjoying an information advantage.

There are several features of the money market that affect the possibility for banks to satisfy their liquidity needs through the available channels. These factors are related to the

[5]Before the changes, the reserve maintenance period started on the 24th of each month and ended on the 23rd of the following month, and was independent of the dates of the Governing Council meeting. Also, the maturity of the weekly main refinancing operation was two weeks. Given that the tenders were conducted at fixed rates, when the market expected an increase in the key policy rates, banks submitted a large number of bids. When there were expectations of interest-rate reductions instead, the bids fell short of the amounts needed to satisfy the reserve requirements. This caused excess volatility of the overnight rates because banks would resort heavily to the market to resolve their liquidity imbalances.

[6]The 2009 Euro Money Market Survey suggests that around 35% of the overall trading activity takes place through bilateral deals, 20% through voice brokers, and 45% through electronic platforms.

[7]The unsecured market involves trading uncollateralized contracts. The secured segment, instead, consists of trades where collateral is posted against interbank lending. The 2009 Euro Money Market Survey reports that around 60% of trades in both the unsecured and the secured segments have a maturity longer than one month.

institutional rules of the ECB supply of liquidity, and to the importance attached to the counterparties' creditworthiness in the money market.

Private financial institutions can take part to the liquidity tenders only if they are listed as eligible counterparties by the ECB.[8] Furthermore, the number of banks eligible to participate in the fine-tuning operations is rather restricted, and is typically limited to a number of from ten to fifteen large banks. In this sense, the operational rules of the ECB generate a discrimination between banks in the access to the primary supply of liquidity. In addition to this factor, banks face administrative costs for taking part to the ECB tenders. These transaction costs can represent a disincentive especially for the small banks.

The rules of the ECB for the conduct of open market operations establish a number of requirements for the participating institutions. Firstly, banks have to post appropriate assets as a collateral. These assets are subject to two types of valuation criteria. They have to carry the required credit rating, and they must have an appropriate value. The ECB applies 'haircuts' to the nominal value of the assets used as collateral. The amount of liquidity received by the participating banks is equal to the nominal asset value minus the haircut. The total value of collateral required to participate in the open market operations is equal to the amount borrowed plus the haircut and the interest paid to the ECB.

Idier and Nardelli (2008) suggest that the possibility for banks to borrow in the unsecured money markets is largely affected by their reputation. As noticed earlier, trading in the unsecured markets operate over the counter. Therefore trust is a relevant factor that determines the matching process between counterparties, and the reputation of banks plays an important role. Market reputation depends on different factors, such as the bank size. Larger banks have both the organizational structure and the knowledge that is needed to put in place comprehensive asset-liability management plans. In this sense, they can obtain a larger advantage from being active traders in the money market.

There is also a geographical factor that generates heterogeneity in the possibility for banks to satisfy their liquidity needs. Despite the introduction of the Euro, there is evidence suggesting that a national bias is still present in the money market. The 2009 Euro Money Market Survey indicates that, on average, 35% of the transactions involve national counterparties both in the unsecured and the secured segments. Around 45% of trades take place between non-national counterparties from the Euro area. This suggests that the banks that do not take part to the open market operations of the ECB can still face some form of rationing in cross-country lending or borrowing.

[8] Idier and Nardelli (2008) report that approximately 2000 financial institutions are eligible for the main refinancing operations, out of the 6500 located in the Euro area. However, only between 340 and 400 institutions take part, while only 148 on average participate to the longer-term refinancing operations.

2.3 The asset traded in the money market

In the unsecured overnight market, assets are peculiar compared to other markets because they consist of contracts. Unlike in the stock market, traders in the money market do not exchange the property of a share value of a firm, whose price is driven by fundamental factors. Rather, a cash transfer takes place between two parties. This transfer carries an interest rate payment. The level of the interest rate determines the value of the contract and characterizes, at the aggregate level, the trade patterns prevailing in the market. The value of the contract depends also on additional factors. These include the current availability of the underlying asset in the market, the individual knowledge about the future developments of asset demand, and about the stance of the liquidity supply of the central bank.

The model is based on the assumption that money market contracts are underwritten at a fair value. In the traditional formulation of Easley and O'Hara (1987), the true value is unobservable, as it is related to the fundamental characteristics of the asset. Defining the true value of a money market contract is somewhat more problematic. Ideally, it represents the shadow value of the equilibrium demand for liquidity of a bank. Since this cannot be measured, I assume that the true value reflects the aggregate liquidity needs of the banking system in normal circumstances.

2.4 The structure of the information set

Two key features of the money market should be considered to understand the role of information. The first factor is that banks that pursue active trading can have an impact on the aggregate demand for liquidity. Banks with large liquidity needs tend to adopt systems of asset-liability management that rely on centralized orders for the money market, and on sophisticated trading strategies. This provides larger banks with additional tools to capture market information, to understand the determinants of the aggregate demand for liquidity, and to disentangle the factors driving the demand from their counterparties. The second relevant aspect is that a superior knowledge of the aggregate liquidity demand also translates in a better ability to predict the future supply of liquidity of the ECB.

The model assumes that bankers update their beliefs on the value of the asset as a response to signals. Depending on their beliefs, they decide whether to trade or not. The type of signal is public information, and does not change during a trading day. A 'high' signal (H) characterizes contracts that are negotiated at rising rates. A 'low' signal (L) instead denotes contracts with a true value that is expected to fall. There are also 'uninformative' days (O) when no signal arises. For these days, I assume that no trading takes place.

Since the structure of information is the motive for trading, the model contemplates three types of banks, namely 'uninformed', 'informed' and 'market makers'. Uninformed banks exchange contracts to comply with the reserve requirement imposed by the central bank. Instead, informed banks are not constrained by reserve requirements, as they are assumed to be close to compliance. These agents use strategic information to influence the bid-ask spread prevailing in the market. Finally, the market makers obtain liquidity mainly from the operations carried out by the central bank (see Idier and Nardelli, 2008). After that, they trade in the private segments of the market. This allows them to quote the best (thinnest) bid-ask spread and to announce it publicly to the market.

The presence of traders with different information sets suggests that uninformed banks face an information risk while trading money market contracts. The reason is that the fraction of banks that can efficiently fulfill future reserve requirements is also more capable of understanding both the aggregate demand for liquidity, and the direction of changes in interest rates. For informed banks, asymmetric information is a source of profits because it generates trading opportunities.

2.5 The trading structure

I assume that the market is made of segments where banks trade contracts of different maturities. In each segment, banks observe the trading process. They assign probabilities of trade origination to the type of order they observe, i.e. whether orders are initiated by informed or uninformed traders. The structure of signals and the trading process are depicted in Figure 1. The probability that an informative trade takes place on a given day is α. When information is revealed, it can lead to a lower price for liquidity with a probability δ. Informed banks enter the market with a probability μ, whereas uninformed trades take place with a probability $1-\mu$. A fraction λ of uninformed trades involves selling liquidity, and a fraction $1-\lambda$ consists of buy trades. Given an uninformed selling signal, there is a fraction ϵ_s of sell transactions and a fraction $1-\epsilon_s$ of no trades. Uninformed buying signals involve effective buy transactions for a fraction ϵ_b of no trades.

From the trading tree, the probability of trading based on a 'high' price signal is

$$\text{prob}\,(B,S,N|s=H) = [\mu + (1-\mu)\lambda\epsilon]^B\,[(1-\mu)\lambda\epsilon]^S\,[2(1-\mu)(1-\epsilon)\lambda]^N\,, \tag{1}$$

and the probability of trading conditional on a 'low' price signal is

$$\text{prob}\,(B,S,N|s=L) = [\mu + (1-\mu)\lambda\epsilon]^S\,[(1-\mu)\lambda\epsilon]^B\,[2(1-\mu)(1-\epsilon)\lambda]^N\,. \tag{2}$$

When the signal is uninformative, the probability of observing trades is instead equal to

$$\text{prob}\,(B,S,N|s=O) = \lambda^{B+S+N}\left[\epsilon^{B+S}(2(1-\epsilon))^N\right]. \tag{3}$$

Assuming that the trading activity is independent across T days, the likelihood of trading activity takes the form

$$\text{prob}\left[\{B_t, S_t, N_t\}_{t=1}^{T} | (\alpha, \delta, \mu, \epsilon)\right] = \prod_{t=1}^{T} \text{prob}\left[\{B_t, S_t, N_t\} | (\alpha, \delta, \mu, \epsilon)\right] \tag{4}$$

In order to reduce the parameter space, the literature typically assumes that the share of uninformed buy and sell transactions is the same, that is $\lambda = 0.5$. I also assume that there is the same probability that uninformed buyers and sellers enter the market ($\epsilon_s = \epsilon_b = \epsilon$). These assumptions deliver the likelihood function

$$\begin{aligned} \mathcal{L}(\alpha, \delta, \mu, \epsilon) = \prod_{t=1}^{T} & \left[(1-\epsilon)^{N_t}(1-\mu)^{N_t} A^{B_t+S_t}\right] \times \\ & \times \left[\alpha(1-\delta)\left(\frac{\mu}{A}+1\right)^{B_t} + \alpha\delta\left(\frac{\mu}{A}+1\right)^{S_t} + (1-\alpha)\left(\frac{1}{1-\mu}\right)^{B_t+S_t+N_t}\right] \end{aligned} \tag{5}$$

with $A = \frac{(1-\mu)\epsilon}{2}$. The likelihood function depends on the number of buy (B_t) and sell-initiated (S_t) orders, and on the number of no trades (N_t). I maximize the likelihood on rolling samples to obtain time-varying estimates of the parameters. The parameters can then be used to compute indices of information asymmetry in the money market.

Following the literature, I measure asymmetric information with the probability of informed trading (PIN_t). This is defined as the unconditional probability that informed traders borrow or lend liquidity at each point in time, and is equal to

$$\text{PIN}_t := \frac{\mu_t}{\Psi_t} \tag{6}$$

The term $\Psi_t := (1-\mu_t)\epsilon_t + \mu_t$ denotes the probability of observing a trade during informed days. When this probability is high, uninformed banks face a lower risk of trading with a counterparty that is better informed.

The time variation of PIN can capture a source of heterogeneity in the learning process of banks. An increasing PIN mimics a situation where a group of banks is able to form interest rate expectations that are increasingly more accurate than those of the rest of the banking system. A fall in PIN, instead, suggests that the learning process becomes more homogenous between banks.

3 The dataset

In this paper I focus on trading behaviour through bilateral deals in the unsecured segments for interbank deposits. Since trading is over-the-counter, data on effective prices and volumes are unavailable to the general public. Only quotes for bid and ask prices can be obtained from reliable sources. I use this type of dataset because it provides a more adequate picture on the role of reputation in the market, which is one of the key factors that drives bilateral trading in the unsecured segment.

Several studies employ high-frequency data from e-Mid, the electronic market for unsecured interbank deposits in the Euro area (e.g., see Baglioni and Monticini, 2008; Beaupain and Durré, 2008; Angelini, Nobili and Picillo, 2009). The rules for access to e-Mid require banks to have net assets worth more than 10 million U.S. dollars. This prevents smaller banks from operating in e-Mid. As suggested earlier, differences in size can affect that ability of banks to acquire information on the prospective demand for liquidity. For instance, larger banks can face a wider pool of trading counterparties. Thus, the data from e-Mid would not account properly for the sources of heterogeneity in the money market.

The dataset used here consists of Reuters quotes on unsecured lending with maturity of 1, 3, 6 months and 1 year. The information available includes best bid and ask prices, and the time stamp sampled at a 5-minute frequency. In order to restrict the sample to the trading hours when most of the trading takes place, intraday quotes are available from 8am to 7pm CET. This provides 120 intraday data points. The dataset spans from November 11 2000 to March 18 2008. There are 1921 daily observations, out of which 1761 for the subsample until August 8 2007 and 160 for the subsample after August 8 2007.

3.1 The classification of trades

The maximization of the likelihood function requires data on the order flow, namely the number of buy- and sell-initiated trades and no orders. Since this information is not directly available, I apply the method for trade classification proposed by Lee and Ready (1991). For this purpose, I assume that quoted bid and ask prices are driven mainly by inventory constraints. This assumption implies that banks hold liquidity at a level close to the optimal size.

Idier and Nardelli (2008) suggest that five cases of trade classification are possible. An increase in both ask and bid prices indicates that dealers are willing to sell the contract at a price higher than in the previous transaction. This reflects a buy order, or a borrowing contract. A fall in both ask and bid prices, instead, suggest that a sell order or a lending contract takes place. An increase in the ask and a decrease in the bid is classified according to the relative size of the change. If the positive increase in the ask is larger (lower) than the decrease of the bid in absolute value, then the trade is classified as buy (sell) initiated. If the positive increase in the bid is larger (smaller) than the fall in the ask price, then the trade is classified as buy (sell) initiated. Finally, symmetric changes or no changes at all in bid and ask prices indicate no trading.

Figure 2 plots the distribution of the classified trades for the four contract maturities. Table 1 reports some descriptive statistics for these distributions. Like in the case of the overnight segment, all the distributions are largely skewed and leptokurtic (see Idier and Nardelli, 2008). This is indicative of higher concentration of trading activity in particular days.

4 Results

I maximize the likelihood function 5 using the simulated annealing algorithm described in Goffe et al. (1994). The standard errors are computed by evaluating the analytical derivative of the likelihood at the maximum. Table 2 reports the parameter estimates for the full sample. The estimated α indicates that the number of days when trading is information-driven increases from 20% for 1-month contracts to over 30% for 1-year contracts. The probability δ of observing a low signal also rises as a function of contract maturity. This means that, for longer maturities, banks perceive a larger portion of excess liquidity in the market. The fraction μ of trades based on asymmetric information is low, and decreases from nearly 17% for one-month to 12% for one-year contracts. The parameter ϵ represents the probability that a trading counterparty in the money market is uninformed. This probability is high for the 1-month contract, and falls drastically along the maturity profile. During uninformed days, the demand for liquidity is driven by 17% of trades from uninformed banks. The last column of Table 2 reports the probability that bilateral trades are based on private information. The PIN increases for longer maturities. In other words, the ability of banks to predict future interest rates and liquidity needs becomes more disperse for longer maturities.

In order to account for time variation in the learning mechanism of market participants, I estimate the trading model on rolling samples of 200 trading days.[9] The parameter estimates are depicted in Figures 3-6. Figure 3 shows that, For contracts with one month and three months of maturity, the share of informed days α is somewhat variable until 2006. The rolling estimates have a peak at the beginning of 2007, and then fall to the average levels prevailing before the turmoil. The surge starting in the beginning of 2007 takes place also for the six-month and one-year maturities. However, for these two contracts, the estimated α is rather volatile across the full sample. Figure 4 plots the time profile of δ. Following the reform of the operational framework of 2004, the probability of a low signal rises for most of the maturities until the end of 2005, and it starts falling until the end of the sample. The one-year contract is an exception to this. In this case, the probability of a low signal falls until June 2006 and rises again until April 2007. The time-varying estimates of the proportion μ of informed banks are reported in Figure 5. It is clear that the reform of 2004 is followed by an increase in the fraction of informed banks for all the contracts. The estimates of μ start falling around the introduction of the loose liquidity policy of October 2005, and turn to a rising trend from the beginning of 2007. The estimated fraction of non-informed trades ϵ in uninformed days are depicted in Figure 6. The maturity contracts from one to six months are characterized by the same pattern. In particular, the estimated ϵ increases until the introduction of the 2004 reform of the operational framework, and starts to fall after

[9] The pattern of the rolling estimates is broadly similar for windows of 50, 70, 300 and 400 trading days.

2004. For all the maturities, the share of non-informed trades increases from the end of 2005, namely from the beginning of the loose provision of liquidity by the ECB, and falls after the beginning of 2007.

Figure 8 plots the rolling estimates of the probabilities of informed trading. Three stylized facts are common across the maturity spectrum. First, following the implementation of the reform of the operational framework in 2004, the PIN measures stand on an upward trend. This pattern takes place also after the introduction of fine-turning operations at the end of the maintenance period of November 2004. Second, after the beginning of the loose liquidity policy in October 2005, the probabilities of informed trading increase until March 2006 and drop until the middle of 2007. Finally, the measures of PIN start rising after the eruption of the current turmoil in the Euro area money markets in August 2007.

The upward trend in PINs after the 2004 reform is puzzling. The share of informed banks increases for all the maturities until November 2004. The evolution of the share of uninformed trades is instead characterized by a larger variability, and varies strongly across maturities. These considerations suggest that the pricing of interbank loans has become more stable in correspondence with a wider heterogeneity in the banking system.[10]

These patterns are similar to those documented by Idier and Nardelli (2008) for the overnight segment. The intuition for these results is that the reform has contributed to the creation of a larger pool of banks capable of understanding the developments of the market. The effects of the practice of frequent FTOs are twofold. On the one hand, FTOs fuel the heterogeneity in the banking sector because these operations involve only a small number of counterparties. On the other, FTOs are typically liquidity-absorbing. This provides an incentive for banks to focus on the fulfillment of the forthcoming reserve requirements, and on complying with the outstanding cash flow commitments, rather than on trading for strategic purposes. Overall, the first effect prevails by creating the incentives for a heterogeneous learning process in the banking system after the 2004 reform.

Figure 8 depicts also the evolution of the monetary policy stance of the ECB, in the form of the minimum bid rate. The probabilities of informed trading have a systematic relation with the policy cycle. For contract maturities below one year, the beginning of the loosening cycle in the middle of 2003 is followed by a drop of information heterogeneity. Instead, for one-year deposits, the PIN follows a rising trend that starts in 2004. The beginning of the tightening cycle in 2006 is anticipated by all the market segments as information risk starts increasing in 2005. The positive correlation between the index of asymmetric information and the minimum bid rate breaks down in the beginning of 2006, when the PINs start falling.

Table 3 reports some descriptive statistics of the rolling PINs. All the probabilities

[10]The discussion introduces an interesting hypothesis on the link between extreme bidding behavior in the weekly MROs before the reform and asymmetric information. In particular, there is the issue of whether informed banks practiced overbidding or underbidding to anticipate the demand for funds from their trading counterparties due to expected future interest rate changes. This problem is left for investigation in future work.

of trading based on asymmetric information are left-skewed. This means that there is a concentration towards high values of the PINs. As expected from Figure 8, the probabilities of informed trading are strongly correlated across maturities. I also investigate the degree of persistence by computing the unit root tests of Dickey and Fuller (1979). For this purpose, I estimate auxiliary regressions with only a constant, and both a constant and a time trend. Table 4 reports the test statistics and p-values. The null of a unit root is never rejected, thus indicating that exogenous change to PINs exert long-lasting effect across trading days.

It is instructive to investigate whether the PIN estimates differ across groups of contracts. I divide the interbank deposits into four groups for contract maturity, and into three groups for the bid-ask spread. For the spread, I rank all the contracts by their average daily spread and divide them into three groups of equal size with low, medium, and high values of the spread. Figure 9 plots the cumulative distributions of the contracts grouped by maturity and by the spread. Interestingly, panel 9(b) shows that the deposits with higher spreads are associated with higher PINs.

The cumulative distributions of the groups are compared by computing the test of Kruskal-Wallis and the Wilcoxon rank-sum test. The Kruskal-Wallis test is based on the null hypothesis that the groups are drawn from identical populations. The null is rejected if one or more population distributions differ from the others. The Wilcoxon rank-sum statistic tests the null hypothesis that two sample groups are drawn from identical populations against the alternative that one population has a higher average PIN. Tables 5 and 6 report the results of the Kruskal-Wallis and the rank-sum test, respectively. The null hypotheses of both tests are strongly rejected for all the groups. This indicates that the differences in PINs across contract maturities and bid-ask spreads are statistically significant.

In order to understand what moves the probabilities of informed trading, I consider the role of the cyclical patterns of liquidity demand, supply of liquidity, and money market volatility. I also study the effect of information asymmetries on bid-ask prices and money market returns.

4.1 The role of calendar effects and the supply of liquidity

In this section I investigate whether the institutional features of the money market drive the patterns of information asymmetry. As a starting point, I study the relation between the PINs and the calendar effects that are known to affect the demand for liquidity in the Euro area. As stressed earlier, at the end of the maintenance period, the reserve requirement becomes binding, and banks react more strongly to liquidity shocks. Hence, day-specific patterns of high liquidity demand arise typically at the end of the maintenance period (see Durré and Nardelli, 2008). The presence of systematic calendar-day tensions in the money market can provide informed banks with an opportunity to learn about their counterparties, and to exploit their trading capabilities.

I model the relation between the PIN for different contract maturities and the calendar effects with linear regression models, where calendar effects are included in the form of dummy variables. I consider three types of dummies that identify features of calendar patterns. The first type $D_{6-\mathrm{day},t}$ takes the value 1 for the six days before the end of the maintenance period, and zero otherwise. The second type of dummy $D_{\mathrm{lastdays},t}$ assigns the value 1 to the days between the last main refinancing operation and the end of the maintenance period, and zero otherwise. Finally, the dummy $D_{\mathrm{endm},t}$ takes the the value 1 for the last business day of each month, and zero otherwise. Since the turmoil may have affected the trading patterns arising from calendar effects, I control for the beginning of market turbulence, and I include an interaction term with the calendar dummy. The dummy $D_{\mathrm{turmoil},t}$ takes the value 1 from August 8 2007 until the end of the sample, and zero in the previous period. Suppose we are interested in the relation between the last 6 days of the maintenance period and the PIN for a given maturity contract. The regression model is

$$\mathrm{PIN}_t = c_1 + c_2 D_{6-\mathrm{day},t} + c_3 D_{\mathrm{turmoil},t} + c_4 \left(D_{6-\mathrm{day},t} \times D_{\mathrm{turmoil},t}\right) + \epsilon_t. \tag{7}$$

Table 7 reports the parameter estimates. All the estimated coefficients have a positive sign and are statistically-significant. This suggests that the presence of money market pressures on the buy side at the end of the maintenance period reveals additional information to informed banks. The turmoil has enhanced this source of asymmetric information.

Since October 2005, the ECB has implemented a loose liquidity policy by supplying funds above the benchmark allotment. Moreover, the demand pressure in the money market during the turmoil has sparked a variety of policy responses in the form of enhanced liquidity supply. It is thus natural to investigate whether the interbank market has experienced a reduction of asymmetric information when a loose supply of liquidity has taken place. In what follows, I investigate the relation between the probabilities of informed trading and different features of the provision of liquidity of the ECB. I consider the three available types of operations, namely main refinancing, fine-tuning, and long-term refinancing operations. I distinguish between fine-tuning operations that are liquidity-providing and liquidity-absorbing. I also consider open-market operations that supply liquidity above or below the benchmark allocation at allotment. The information for the construction of these dummies is obtained from the ECB website, where a detailed time-series dataset on the open market operations is available.[11] I estimate the regression model 7 with the liquidity supply dummies $D_{\mathrm{mro},t}$ for the main refinancing operations, $D_{\mathrm{fto},t}$ for the fine-tuning operations, $D_{\mathrm{ltro},t}$ for the long-term refinancing operations, $D_{\mathrm{providing},t}$ for the liquidity-providing operations, $D_{\mathrm{absorbing},t}$ for the liquidity-absorbing operations, $D_{\mathrm{supply>bench},t}$ for liquidity-supply operations in excess of the benchmark, and $D_{\mathrm{supply<bench},t}$ for liquidity-supply operations below the benchmark allocation.

Table 8 reports the regression estimates for the dummies that identify the type of open

[11]The detailed dataset is located on http://www.ecb.int/mopo/implement/omo/html/top_history.en.html, and the benchmark allotments can found found on http://www.ecb.int/stats/monetary/res/html/index.en.html.

market operation. The coefficients for the main refinancing operations and the long-term refinancing operations have a positive and significant sign, thus suggesting that banks are capable of acquiring additional information from these operations. Also the estimated coefficients for the fine-tuning operations have a positive sign. However, they are not statistically significant. The turmoil strengthens the reaction of the PINs to the supply of liquidity. Table 9 shows the coefficient estimates for liquidity providing/absorbing fine-tuning operations, and for operations that supply liquidity above or below the benchmark. A tightening of the supply of liquidity to the market in the form of liquidity-absorbing operations, or supply below the benchmark, is not related to information asymmetries. This result holds regardless of the financial turmoil. The intuition is that a buoyant liquidity supply provides trading opportunities in the market for the banks that take part to the ECB tenders, and that do not face liquidity shortages for their asset-liabilities management plans. This allows informed banks to gather additional information on their trading counterparties. On one hand, draining liquidity from the market reduces trading opportunities on one hand. On the other, it increases the dependence of uninformed banks on larger and less constrained institutions.

4.2 Are PINs related to money market volatility?

In this section I study the relation between the probabilities of informed trading and volatility in the money market. The literature on market microstructure suggests that information asymmetry between investors can increase price volatility. Uninformed traders may rationally act like price chasers, which may in turn increase market volatility (e.g., see Wang, 1993). However, volatility may also induce informed banks to trade. In the model of Kyle (1985), the trading decisions of informed agents depend both on the volatility of noise trading, and on the volatility of prices. These considerations suggest that the relation with volatility has implications on the capability of the PIN to capture the patterns induced by information asymmetries.

Following Andersen, Bollerslev and Diebold (2002) and Hanse and Lunde (2006) I approximate the time variation of volatility by computing the measure of realized volatility

$$\mathrm{RV}_{i,t}^{(m)} = \sum_{j=1}^{m} r_{i,t,j}^2 \tag{8}$$

where $r_{i,t,j}$ is the intraday return over a sampling interval of length i, and m is the number of intradaily partitions. The returns are computed as the difference between intraday prices in logarithm, with the prices defined as the midpoints between ask and bid. Figure 10 plots the relation between the PINs and the realized volatilities. The scatter plots show that the measure of asymmetric information has no relation with money market volatility for any contract maturity.

4.3 Do PINs have long-run linkages?

The following question of interest concerns the presence of linkages between information asymmetries for the different maturities. There are several factors that can prevent information segmentation from taking place in the long run. For instance, there can be spillovers across the term structure because information on the aggregate demand for liquidity is maturity-specific. Suppose informed banks have knowledge of a large positive shock to the term demand for liquidity at 1 year. If this was combined with an excess of supply of 6-month dated funds, the informed banks could offer to roll over these term contracts to cover the 1-year dated demand.

The descriptive statistics of the rolling PINs discussed earlier report strong correlation across the maturity structure. The ADF tests indicate that the PINs can be appropriately described by unit root processes. In this section I study whether a long-run relation is present in the form of cointegration. As as starting point, I compute the standard test of Johansen (1988) between pairs of maturities. The auxiliary models include an unrestricted constant and trend.[12] The test statistics are reported in Table 10. The null of a unit root is rejected in all the cases, which suggests that there are no long-run linkages between PINs across the maturity spectrum.

The outcome of the cointegration tests cam be affected by a variety of factors, such as neglected nonlinearity in the relation between two series. Nonlinearity could arise from the presence of systematic periodic patterns that generate large residuals. For this reason, I compute also the tests for nonlinear cointegration of Bierens (1997a,b). The test statistics involved in the approaches of Johansen (1988) and Bierens (1997a,b) are obtained from the solutions of generalized eigenvalue problems, and the hypotheses tested are the same. The main difference is that the approach of Bierens (1997a,b) is nonparametric, and the generalized eigenvalue problem is formulated on the basis of two random matrices that are constructed independently of the data generating process.[13] Two alternative statistics for empirically determining the cointegration rank r are provided. Given the ordered eigenvalues $\hat{\lambda}_{1,m} \geq \hat{\lambda}_{n,m}$ with the parameter m and the dimension of the system n, Bierens (1997a) proposes the lambda-min statistics $\hat{\lambda}_{n-r_0,m}$ for testing the hypothesis

$$H_0(r_0): \; r = r_0, \quad H_1(r_0): \; r = r_0 + 1 \tag{9}$$

The asymptotic null distribution of this test is nonstandard, and its critical values can be found in Bierens (1997a). The testing framework also includes the statistic $g_m(r_0)$ that is used to estimate r consistently. In this paper, I apply the rule of thumb proposed by Bierens

[12]The tests with models with unrestricted constants only produce the same results and are not reported for brevity.

[13]These matrices consist of weighted means of the system variables in levels and first differences and are constructed such that their generalized eigenvalues share similar properties to those in the Johansen (1988) approach.

(1997a) and choose $m = 2n$. Table 11 reports the test statistics. The results rule out strongly the presence of nonlinear cointegration between the probabilities of informed trading.

4.4 The relation between PINs and the pricing of liquidity

The discussion of the previous sections suggests that asymmetric information is a source of information risk in trading. Uninformed traders face a positive probability of finding trading counterparties that enjoy a superior information set on the future evolution of the liquidity stance. As a result, uninformed agents are subject to an information risk premium (see Easley, Hvidkjaer and O'Hara, 2002). In this section I provide some evidence on the role of heterogeneous information for the pricing of interbank deposits.

I start by testing whether the probabilities of informed trading affect the bid-ask spread for each contract maturity. I estimate four regression models that take the form

$$\begin{aligned}\mathrm{SPREAD}_t = c &+ b_1\mathrm{PIN}_t + b_2\mathrm{RV}_t + b_3\mathrm{D}_{\mathrm{turmoil},t}\\ &+ b_4\left(\mathrm{PIN}_t \times \mathrm{D}_{\mathrm{turmoil},t}\right) + b_5\left(\mathrm{RV}_t \times \mathrm{D}_{\mathrm{turmoil},t}\right) + e_t, \qquad (10)\end{aligned}$$

where SPREAD_t denotes the daily bid-ask spread for a given maturity.[14] The dummy variable $\mathrm{D}_{\mathrm{turmoil},t}$ accounts for the change in the explanatory power of both the PIN and realized volatility arising from the financial market turmoil. I use three types of spreads as dependent variable, namely the daily opening, median or closing spread. Since banks may choose the allocation of funds jointly across different maturities, I also model the cross-sectional dimension of the four maturities by estimating the panel regression

$$\begin{aligned}\mathrm{SPREAD}_{i,t} = c &+ b_1\mathrm{PIN}_{i,t} + b_2\mathrm{RV}_{i,t} + b_3\left(\mathrm{D}_{\mathrm{turmoil},t}\right)\\ &+ b_4\left(\mathrm{PIN}_{i,t} \times \mathrm{D}_{\mathrm{turmoil},t}\right) + b_5\left(\mathrm{RV}_{i,t} \times \mathrm{D}_{\mathrm{turmoil},t}\right) + e_{i,t}. \qquad (11)\end{aligned}$$

Table 12 reports the estimated coefficients for equation 10. The estimation results for the panel regression 11 are detailed in Table 13. The standard errors are heteroskedasticity-robust and adjusted for first-order autocorrelation. Two points are worth noting. First, the estimates indicate that the PINs are related to the bid-ask spreads in a statistically-significant way. This finding provides support to the proposition that information risk is priced in the term segments of the Euro money market. Second, there is evidence suggesting that the money market turmoil has affected the relation between the PINs and the bid-ask spreads. The coefficient estimates of both the turmoil dummy and its interaction with the PINs are small but all have a positive sign. This suggests that a buoyant supply of liquidity from a central bank may not be enough to reduce market tensions. The reason is that a loose liquidity

[14] Standard empirical models of information-risk pricing include the traded volumes among the explanatory variables. Since traders typically look at volumes, omitting trading volumes introduces a source of misspecification. However, as stated earlier, information on traded volumes in the OTC segments is not available. The results presented in this section should thus be considered with care.

supply may enhance information asymmetries when information risk is priced.

A more appropriate test for information pricing concerns the relation between returns on interbank deposits and PINs. The risk of trading with counterparties that enjoy superior information can command high returns while manifesting itself in high spreads. Indeed, as discussed earlier, the probabilities of informed trading are correlated with the spreads. However, returns can be driven also by a compensation for exogenous sources of 'illiquidity' or market 'depth' risk that generates high spreads, and that are not captured by the measure of information heterogeneity (see Easley, Hvidkjaer and O'Hara, 2002). To account for these factors, I model the returns r_t of each contract maturity with the regression

$$
\begin{aligned}
r_t = c + b_1\,(\mathrm{PIN}_t) + b_2\,(\mathrm{SPREAD}_t) + b_3\,(\mathrm{RV}_t) + b_4\,(\mathrm{D}_{\mathrm{turmoil},t}) \\
+ b_5\,(\mathrm{PIN}_t \times \mathrm{D}_{\mathrm{turmoil},t}) + b_6\,(\mathrm{SPREAD}_t \times \mathrm{D}_{\mathrm{turmoil},t}) \\
+ b_7\,(\mathrm{RV}_t \times \mathrm{D}_{\mathrm{turmoil},t}) + e_t. \qquad (12)
\end{aligned}
$$

I also estimate a panel model for the four maturities

$$
\begin{aligned}
r_{i,t} = c + b_1\,(\mathrm{PIN}_{i,t}) + b_2\,(\mathrm{SPREAD}_{i,t}) + b_3\,(\mathrm{RV}_{i,t}) + b_4\,(\mathrm{D}_{\mathrm{turmoil},t}) \\
+ b_5\,(\mathrm{PIN}_{i,t} \times \mathrm{D}_{\mathrm{turmoil},t}) + b_6\,(\mathrm{SPREAD}_{i,t} \times \mathrm{D}_{\mathrm{turmoil},t}) \\
+ b_7\,(\mathrm{RV}_{i,t} \times \mathrm{D}_{\mathrm{turmoil},t}) + e_{i,t}. \qquad (13)
\end{aligned}
$$

The parameter estimates of the regressions 12 and 13 are reported in Tables 14 and 15, respectively. The probabilities of informed trading have a statistically-significant relation with the returns. The returns are also positively affected by market depth and volatility. It should be stressed that the bid-ask spread still retains explanatory power despite the inclusion of the PIN among the explanatory variables. The turmoil has enhanced the role of the information risk for the pricing of interbank deposits. In fact, the estimated coefficients of the interactions between the dummies and the explanatory variables are all positive and significant at standard confidence levels.

Additional tests of information risk pricing concern the out-of-sample predictability of the PIN for the bid-ask spreads and the returns. I approach this issue from two different angles. First, I focus on the random walk hypothesis as a competing prediction for the returns. In other words, I study whether a predictive model with only a constant and the PIN generates a superior performance with respect to a random walk. Second, I compare the forecast errors between regression models extended with additional variables, such as realized volatility. In this case, the aim is to understand whether the PINs enhance the predictive performance of models 10 and 12, or whether nested models without the PINs forecast better.

In the comparison with the random walk, I estimate regressions with the first differences of the spreads or the levels of returns and the PINs for each contract maturity

$$\Delta\text{SPREAD}_{t+h} = c_1 + c_2\,(\Delta\text{PIN}_t) + e_t, \tag{14}$$

$$r_{t+h} = c_1 + c_2\,(\Delta\text{PIN}_t) + e_t, \tag{15}$$

where h is the predictive horizon, and Δ denotes the difference operator. The specification with differences is needed to ensure stationarity, which is a prerequisite for the statistical tests of out-of-sample predictability used here. For reasons of brevity I focus on the predictive power of the PINs for 1, 2, and 3 days ahead. Also, I report the results for only the daily closing spreads.[15]

The models 14 and 15 can be affected by parameter instability. For this reason I compute the tests for one-time structural breaks of Andrews (1993), Andrews and Ploberger (1993) and Nyblom (1989). To study the out-of-sample predictability, I run the tests for forecast comparisons between nested models proposed by Clark and McCracken (2001). The non-nested models are represented by equations 14 and 15, and the nested models are random walks

$$\Delta\text{SPREAD}_{t+h} = c_1 + e_t, \tag{16}$$

$$r_{t+h} = c_1 + e_t. \tag{17}$$

To account for the possibility that the regression parameters change over time, I compute also the optimal tests of Rossi (2005) for the null of parameter stability and no difference in predictive content between the nested models. These are the optimal Exponential Wald test, the optimal Mean Wald test, and the optimal Nyblom test. These tests are applied to split-sample, recursive and rolling forecasting schemes.[16] The rolling windows include 50 observations, which corresponds to roughly 3 maintenance periods.

Tables 16 and 17 report the test statistics and p-values for the models of the spreads and the returns, respectively. The first part of each table indicates the results of the tests for parameter stability. The zero p-values for all of the predictive horizons suggest the models suffer from structural instability. Hence, my comments focus on the forecast-encompassing tests based on rolling-windows estimates. The second panel of Tables 16 and 17 show that the nesting models deliver statistically-significant predictive gains with respect to the random walk for most of the horizons. It should be stressed that the negative sign of the test statistics indicates that the mean squared forecast errors of the random walk are larger than those of the nesting models. The third part of Tables 16 and 17 reports the outcome of the tests of parameter stability and predictive power. The low p-values provide evidence for time-varying

[15] The results for the daily opening and median spreads are not included for brevity, and are available from the author upon request. It should be stressed, though, that the predictive power of the PIN for these spreads still stands.

[16] The rolling window includes 200 trading days, as in the previous sections of paper. The test of Diebold and Mariano (1995) is not computed because it does not apply to comparisons between nested models.

predictability of the PIN for the closing-day spread and the returns.

In the following step, I investigate whether the out-of-sample forecasting power of the PINs arises because they are proxies for the predictive content of omitted variables, such as realized volatility or the bid-ask spread. I compute the test of Clark and McCracken (2001) for the two unrestricted models

$$\Delta\text{SPREAD}_{t+h} = c + b_1 (\Delta\text{SPREAD}_t) + b_2 (\Delta\text{PIN}_t) + b_3\text{RV}_t + e_t, \tag{18}$$

$$r_{t+h} = c + b_1\text{r}_t + b_2 (\Delta\text{SPREAD}_t) + b_3 (\Delta\text{PIN}_t) + b_4\text{RV}_t + e_t. \tag{19}$$

I compare model 18 with two nested specifications where either the PIN or the realized volatility is the sole predictor. Model 19 is instead compared with a restricted model where the regressors are either the PIN alone, or the remaining variables without the PIN. Table 18 reports the results of the four comparisons of predictive ability with models estimated on rolling windows. Panels (a) and (b) show that the PIN delivers predictive gains when it is combined with the realized volatility and the spread. In fact, the negative sign of the test statistics suggests that the models with the PIN as the only explanatory variable underperform the encompassing models. Panels (c) and (d) of Table 18 indicate that including the PIN in the predictive model is essential for generating a superior predictive performance. This confirms that the PIN has additional forecasting power that does not stem from that of alternative predictors.

5 Conclusion

The recent turmoil in financial markets has prompted an interest in the functioning of interbank markets. Only a small number of studies is currently available on the microstructure of money markets. In this paper, I extend the results of Idier and Nardelli (2008) by focusing on lending contracts for maturities longer than the overnight. Building on the work of Easley and O'Hara (1992), I estimate the probabilities of informed trading for unsecured lending with maturities of 1, 3 and 6 months, and 1 year.

The money market represents an ideal field of application for the model of Easley and O'Hara (1992). The institutional organization of the market contemplates a primary supply of liquidity by the ECB. The allocation of liquidity to the banking system is discriminatory. However, banks need funds for carrying out their current and planned operations. Heterogeneity among banks in the access to the central bank's operations generates a bottleneck in the trading segments of the money market. Larger banks can participate to the liquidity tenders of the ECB. Moreover, they enjoy a better reputation in the market place because of their balance sheet size. While they trade with smaller banks, they can learn about the determinants of the liquidity imbalance in the system. These considerations suggest that larger banks can enjoy asymmetric information on market developments.

Four main results are obtained in the paper. I show that the asymmetries within the banking sector have decreased across the term structure since 2004. As discussed by Idier and Nardelli (2008), this can be explained by the interplay between the implementation of the reform of the operational framework and the introduction of frequent FTOs at the end of the maintenance period. I find that information heterogeneity is maturity-specific. The probabilities of finding a counterparty with a better information set are strongly correlated along the term structure of interbank lending. However, they have no long-run relation. This suggests that information is segmented in the long run, in the sense that each contract maturity carries information that is not incorporated in other maturities. The results also indicate that banks obtain additional information on days when open market operations are carried out, and at the end of the maintenance period. Furthermore, the policy of loose liquidity supply of the ECB has enhanced the scope for information asymmetries. This effect has strengthened during the turmoil. Finally, I also show that the probability of informed trading contains predictive information for the bid-ask spread and for returns on interbank deposits. This introductory evidence suggests that information risk is priced in the money market.

Several extensions to the analysis detailed here can be envisaged. The issue of pricing of information risk is the key for an in-depth understanding of price formation. The use of a dataset with indicative quotes prevents the paper from obtaining robust results on information risk pricing. In a related work-in-progress, I use a dataset of recorded bilateral transactions provided by e-Mid to estimate a capital asset pricing model for interbank deposits where traded volumes are included among the explanatory variables. Data on effective bilateral transactions also allow to model additional aspects of the microstructure of the money market. Easley et al. (1996) suggest that traders may optimally pool their trades instead of separating them. As a consequence, trade size can affect the estimation of the probability of informed trading. It would be interesting to incorporate a standard model of monetary policy expectations in the pricing of longer-term lending contracts. Another relevant issue concerns the interplay between microstructure factors and the ECB supply of liquidity. In this sense, it would be important to provide a framework where asset-liability management plans for the informed banks interact with the demand for liquidity from uninformed counterparties.

The paper also suggests that the probabilities of informed trading are related to the ability of banks to understand public information better than their market counterparties. One of the main sources of public knowledge consists in the communication policy of the ECB and is, thus, related to the degree of transparency of monetary policy. Transparency implies that financial markets are provided with the tools to better understand monetary policy decisions. Ultimately, this improves the ability of the markets to predict the future course of the policy rates. At the same time, this also reduces the scope for information asymmetries in the determination of the term structure of money market rates. In future work, I am planning to study the heterogeneity in the dissemination of public information throughout the money market. In particular, the relation between the communication policy of the ECB and the probabilities of informed trading can generate insights on the ability of banks to interpret the statements in a heterogeneous fashion.

References

Alonso, F., and R. Blanco (2005), "Is the Volatility of the EONIA Transmitted to Longer-Term Euro Money Market Rates?", *Working Paper*, Bank of Spain, No. 541.

Andersen, T., T. T. Bollerslev, and F. Diebold (2002), "Parametric and Nonparametric Mesurement", *NBER Working Paper*, No. 279.

Andrews, D. W. K. (1993), "Tests for Parameter Instability and Structural Chage with Unknown Change Point", *Econometrica*, 61, 821–56.

Andrews, D. W. K., and W. Ploberger (1993), "Optimal Tests when a Nuisance Parameter is Present only under the Alternative", *Econometrica*, 61, 1383–1414.

Angelini, P., A. Nobili, and M. C. Picillo (2009), "The Interbank Market After August 2007: What Has Changed and Why?", *Banca d'Italia Working Paper*, No. 731.

Baglioni, A., and A. Monticini (2008), "The intraday price of money: Evidence from the e-MID market", *Journal of Money, Credit and Banking*, 40 (7), 1533–1540.

Beaupain, R., and A. Durré (2008), "The interday and intraday patterns of the overnight market: Evidence from an electronic platform", *ECB Working Paper*, No. 988.

Bierens, H. J. (1997a), "Nonparametric Cointegration Analysis", *Journal of Econometrics*, 77, 379–404.

Bierens, H. J. (1997b), "Testing the Unit Root with Drift Hypothesis against Nonlinear Trend Stationarity with an Application to the US Price Level and Interest Rate", *Journal of Econometrics*, 81, 29–64.

Brousseau, V. (2006), "The spectrum of Euro-Dollar", in Gilles Teyssière and Alan P. Kirman (eds.), *Long Memory in Economics*, Springer-Verlag, 69–107.

Cassola, N., and C. Morana (2006), "Volatility of Interest Rates in the Euro Area: Evidence from Hight Frequency Data", *The European Journal of Finance*, 12 (6-7), 513–528.

Cassola, N., and C. Morana (2009), "Comovements in Volatility in the Euro Area Money Market", Forthcoming, *Journal of International Money and Finance*.

Clark, T. E., and M. W. McCracken (2001), "Tests of Equal Forecast Accuracy and Encompassing for Nested Models", *Journal of Econometrics*, 105 (‘), 85–110.

Dickey, D. A. and W. A. Fuller (1979), "Distribution of the Estimators for Autoregressive Time Series with a Unit Root", *Journal of the American Statistical Association*, 74, 427–431.

Diebold, F. X., and R. S. Mariano (1995), "Comparing Predictive Accuracy", *Journal of Business and Economic Statistics*, 20 (1), 134–44.

Durré, A., and R. Pilegaard (2003), "Estimating Riks Premia in Money Market Rates", *ECB Working Paper*, No. 221.

Durré, A., and S. Nardelli (2008), "Volatility in the Euro Area Money Market: Effects from the Monetary Policy Operational Framework", *International Journal of Finance and Economics*, 13 (4), 2008, 307–322.

Easley, D., and M. O'Hara (1987), "Price, Trade Size, and Information in Securities Markets", *Journal of Financial Economics*, 19 (1), 69–90.

Easley, D., and M. O'Hara (1992), "Time and the Process of Security Price Adjustment", *Journal of Finance*, 47 (2), 577–605.

Easley, D., S. Hvidkjaer, and M. O'Hara (2002), "Is Information Risk a Determinant of Asset Returns?", *Journal of Finance*, 57 (5), 2185–2221.

Easley, D., N. M. Kiefer, M. O'Hara, and J. B. Paperman (1996), "Liquidity, Information, and Infrequently Traded Stocks", *Journal of Finance*, 51 (4), 1405–1436.

European Central Bank (2005a), "The Volatility of the Overnight Interest Rate from a Medium-Term Perspective", *Monthly Bulletin*, March 2005, 25–27.

European Central Bank (2005b), "The Transmission of Overnight Interest Rate Volatility to Longer-Term Interest Rates in the Euro Area Money Market", *Monthly Bulletin*, August 2005, 24–26.

European Central Bank (2006), "The Eurosystem's Operational Framework and the Volatility of the Overnight Interest Rate", *Monthly Bulletin*, July 2006, 24–29.

European Central Bank (2007), "Volatility of the Overnight Interest Rate and its Transmission along the Money Market Yield Curve", *Monthly Bulletin*, August 2006, 26–29.

Glosten, L. R., and L. E. Harris (1988), "Estimating the Components of the Bid/Ask Spread", *Journal of Financial Economics*, 21 (1), 123–142.

Glosten, L. R., and P. R. Milgrom (1987), "Bid Ask and Transaction Price in a Specialist Market with Heterogeneously Informed Traders", *Journal of Financial Economics*, 14 (1), 71–100.

Goffe, W. L., G. D. Ferrie, and J. Rogers (1994), "Global Optimization of Statistical Functions with Simulated Annealing", *Journal of Econometrics*, 60 (1-2), 65–99.

Grammig, J., D. Schiereckc, and E. Theissen (2001), "Knowing Me, Knowing You: Trader Anonymity and Informed Trading in Parallel Markets", *Journal of Financial Markets*, 4 (4), 385–412.

Hansen, P. R., and A. Lunde (2006), "Realized variance and market microstructure noise", *Journal of Business and Economic Statistics*, 24, 127–161.

Heider, F., M. Hoerova, and C. Holthausen (2009), "Liquidity Hoarding and Interbank Market Spreads: The Role of Counterparty Risk", *ECB Working Paper*, No. 1126.

Heider, F., and M. Hoerova (2009), "Interbank Lending, Credit Risk Premia and Collateral", *International Journal of Central Banking*, 5 (4), 1–39.

Huang, R. D., and H. R. Stoll (1997), "The Components of the Bid-Ask Spread: A General Approach", *Review of Financial Studies*, 10 (4), 995–1034.

Idier, J., and S. Nardelli (2008), "Probability of Informed Trading on the Euro Overnight Market Rate", *ECB Working Paper*, No. 987.

Jardet, C., and G. Le Fol (2008), "Euro Money Market Interest Rates Dynamics and Volatility: How They Respond to Recent Changes in the Operational Framework", *Banque de France Working Paper*, No. 167.

Johansen, S. (1988), "Statistical Analysis of Cointegration Vectors", *Journal of Economic Dynamics and Control*, 12 (2-3), 231–254.

Jones, C. M., G. Kaul, and M. L. Lipson (1994), "Information, Trading, and Volatility", *Journal of Financial Economics*, 36 (1), 127–154.

Kyle, A. S. (1985), "Continuous Auctions and Insider Trading", *Econometrica*, 53 (6), 1315–1335.

Lee, C. M. C., and M. J. Ready (1991), "Inferring Trade Direction from Intraday Data", *Journal of Finance*, 46 (2), 733–746.

Newey, W., and K. J. West (1987), "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix", *Econometrica*, 55 (3), 703–708.

Nyblom, J. (1989), "Testing for the Constancy of Parameters over Time", *Journal of the American Statistical Association*, 84, 1989.

Rossi, B. (2005), "Optimal Tests for Nested Model Selection with Underlying Parameter Instability", *Econometric Theory*, 21 (5), 962–990.

Sargan, J. D., and A. Bhargava (1983), "Testing for Residuals from Least Squares Regression Being Generated by Gaussian Random Walk", *Econometrica*, 51 (1), 153–174.

Wang, J. (1993), "A Model of Intertemporal Asset Prices under Asymmetric Information", *Review of Economic Studies*, 60 (2), 249–282.

White, A. (1980), "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity", *Econometrica*, 48 (4), 817-838.

Zagaglia, P. (2010), "Money-Market Segmentation in the Euro area: What Has Changed during the Turmoil?", Forthcoming, *Applied Economics Letters*.

Figure 1: Representation of the trading sequence

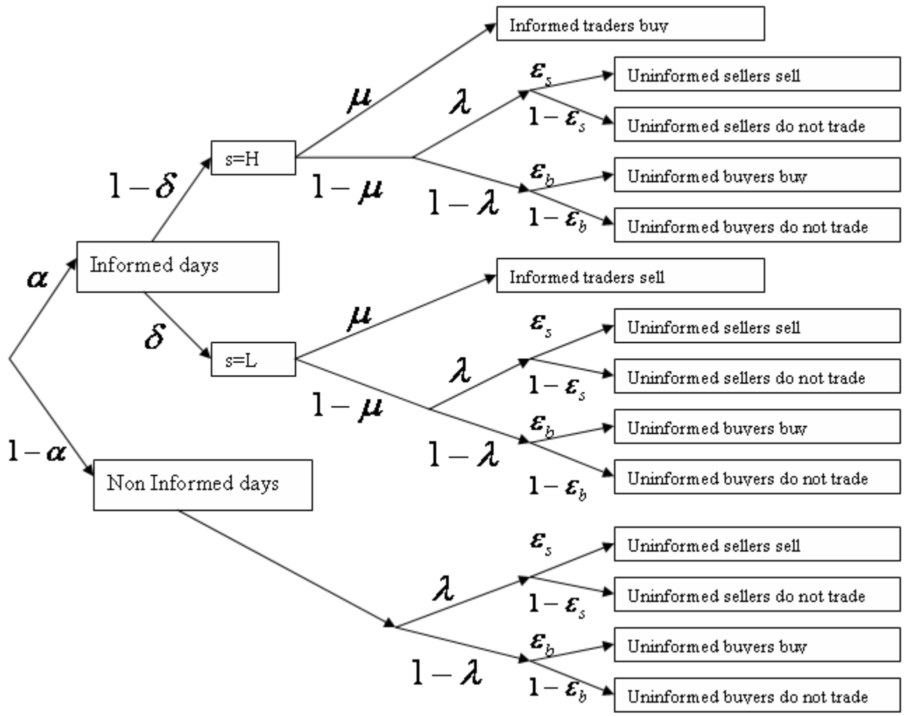
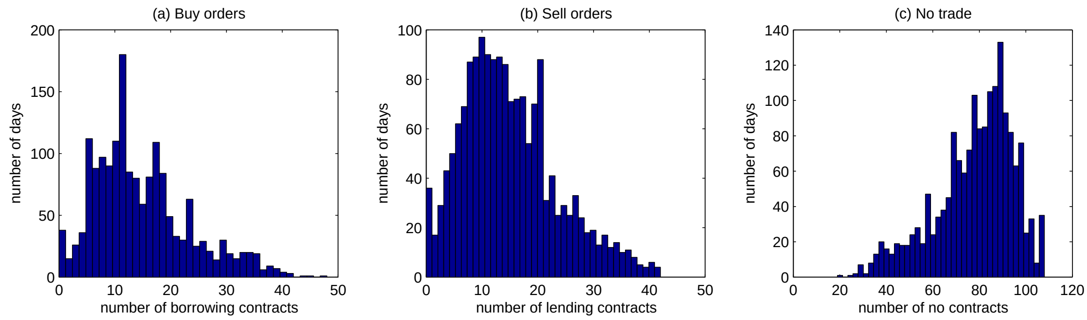
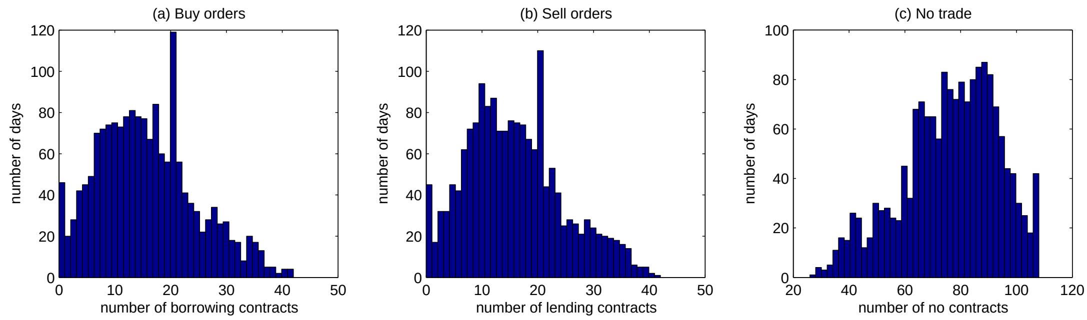


Figure 2: Distribution of trades

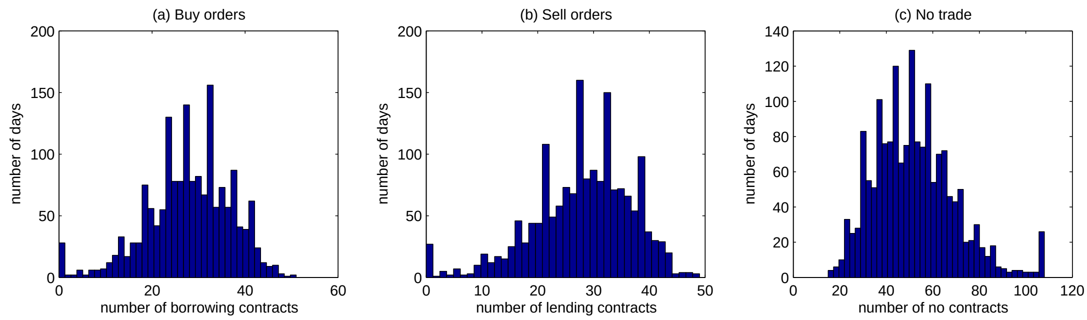
(a) One-month maturity



(b) Three-month maturity



(c) Six-month maturity



(d) One-year maturity

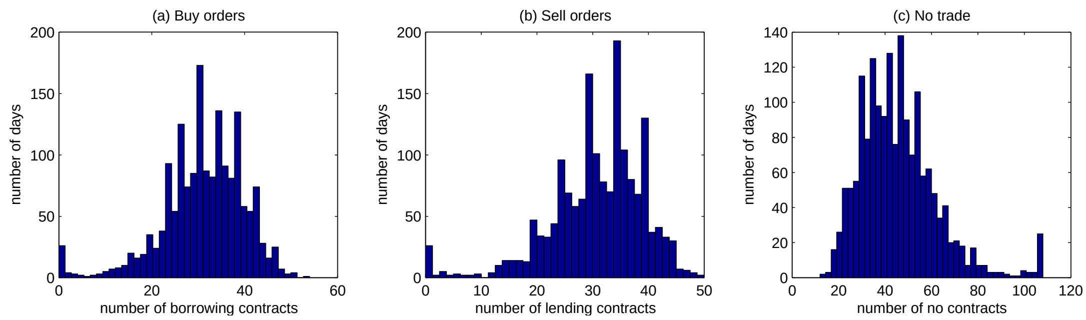
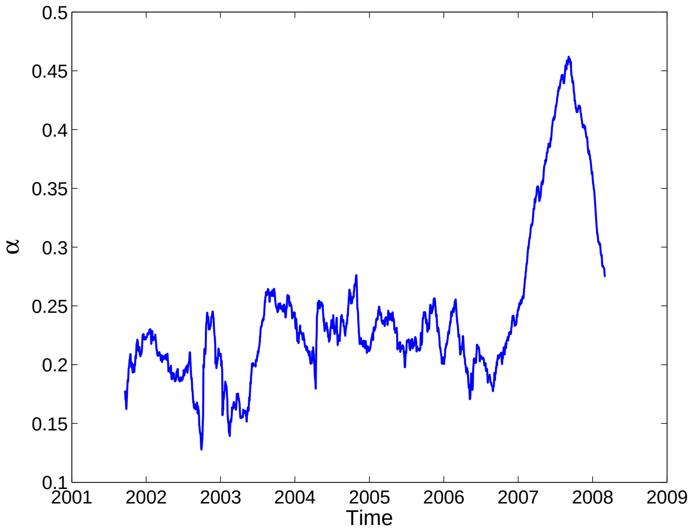
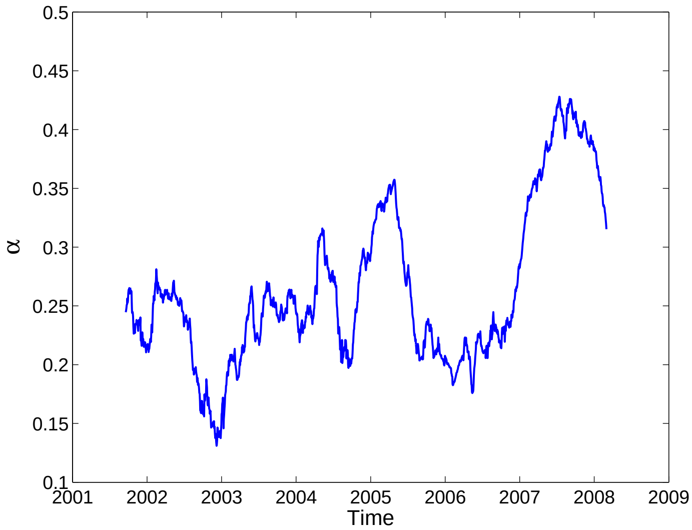


Figure 3: Rolling estimates of the probability α that trades are informative

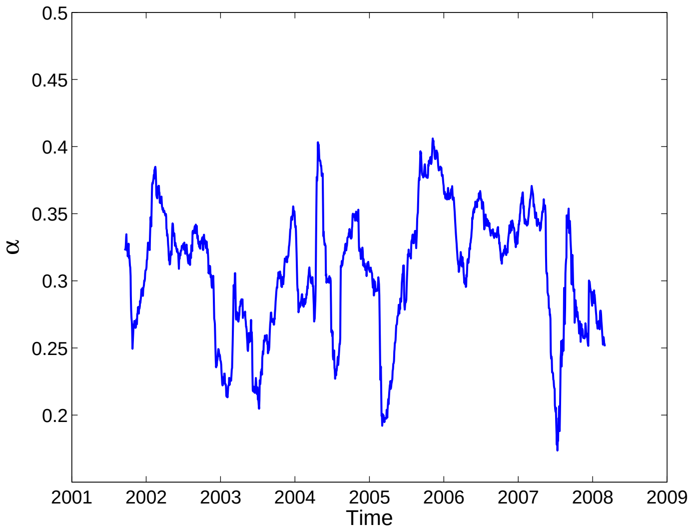
(a) One-month maturity



(b) Three-month maturity



(c) Six-month maturity



(d) One-year maturity

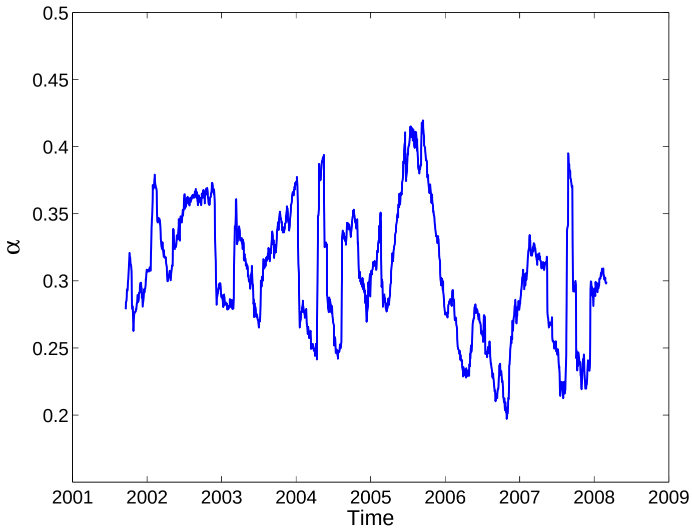


Figure 4: Rolling estimates of the probability δ of a low price signal

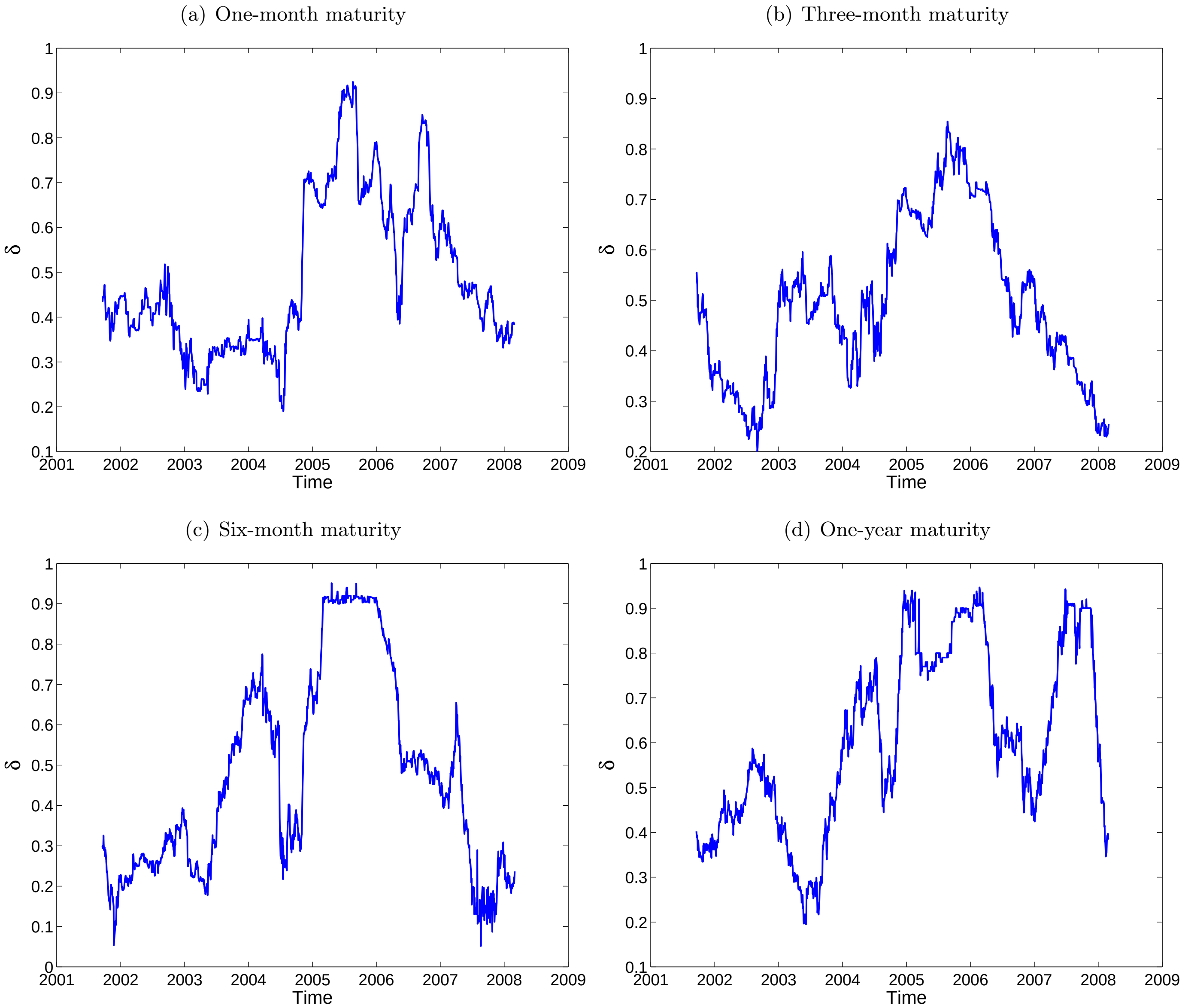


Figure 5: Rolling estimates of the share μ of informed banks that enter the market on informed days

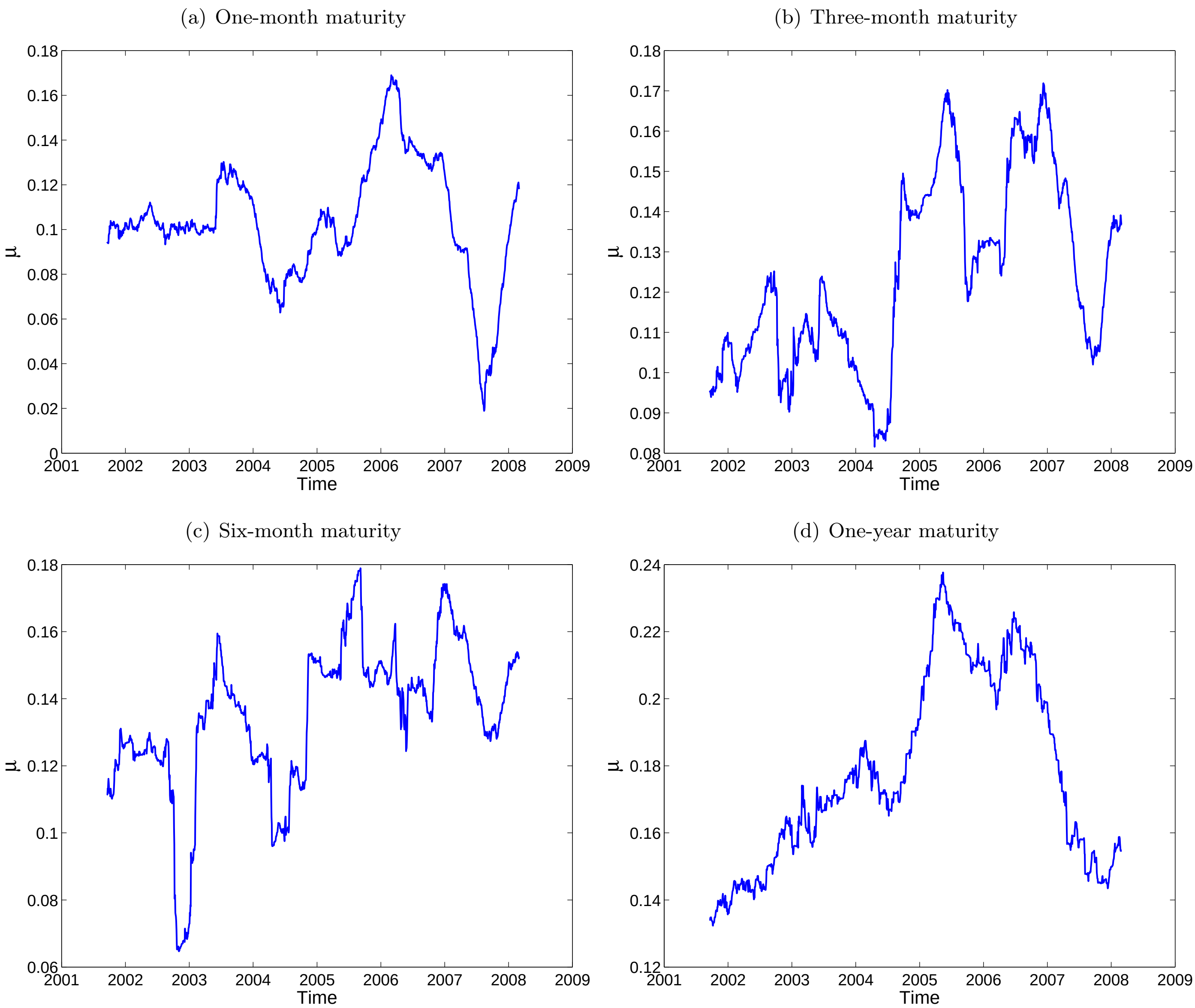


Figure 6: Rolling estimates of the share ϵ of uninformed banks that take part to the market

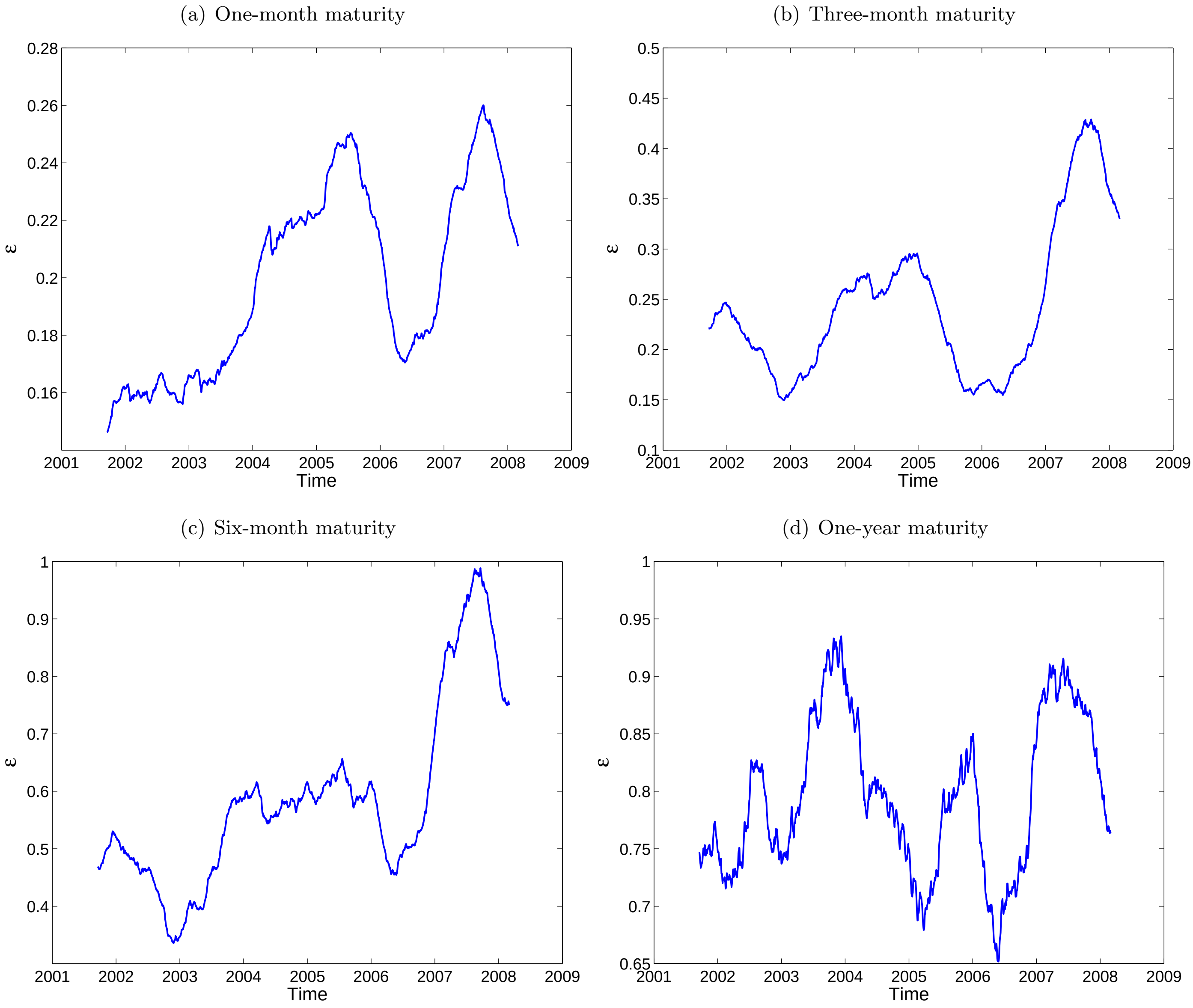


Figure 7: Rolling estimates of the market liquidity measure Ψ

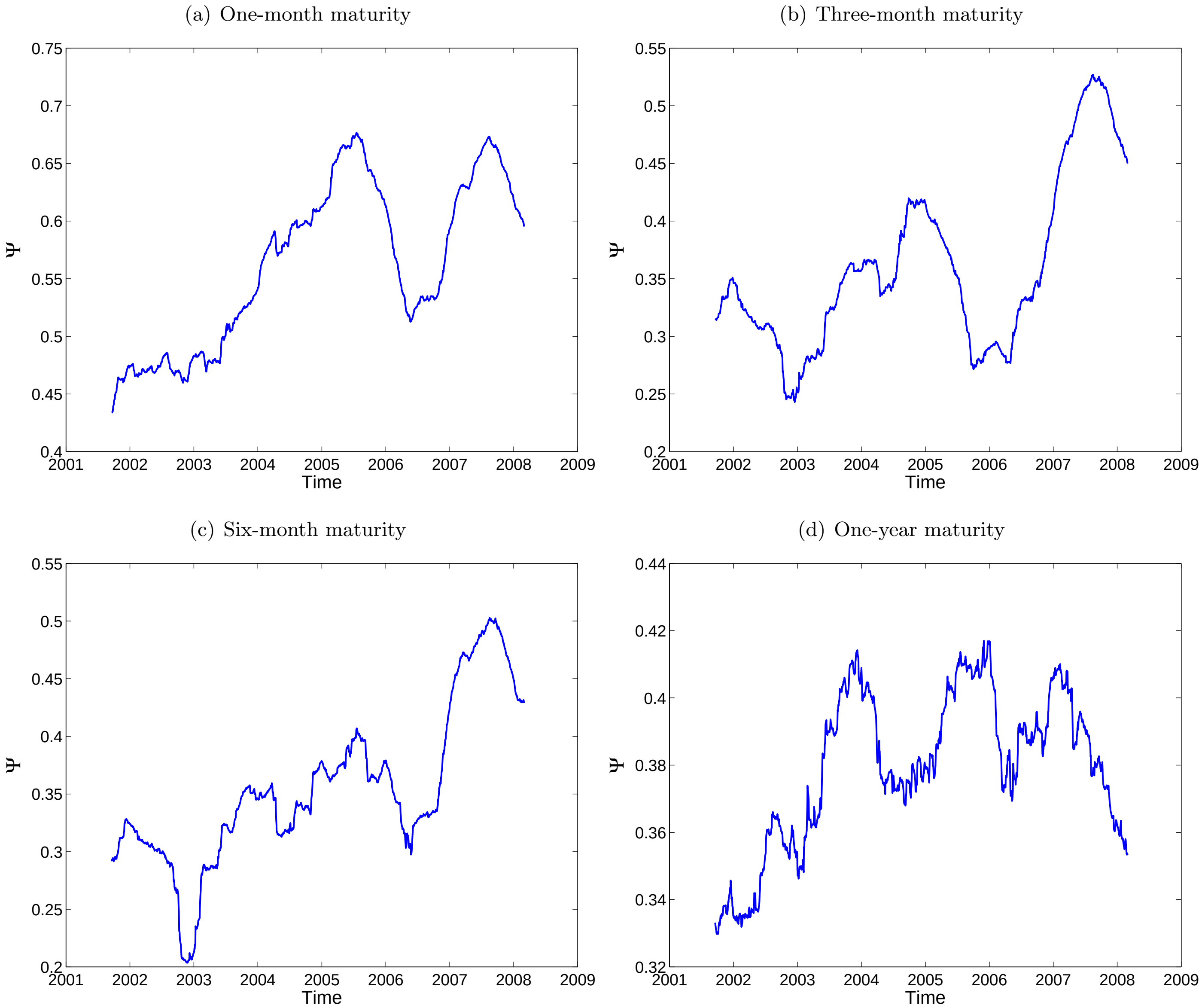
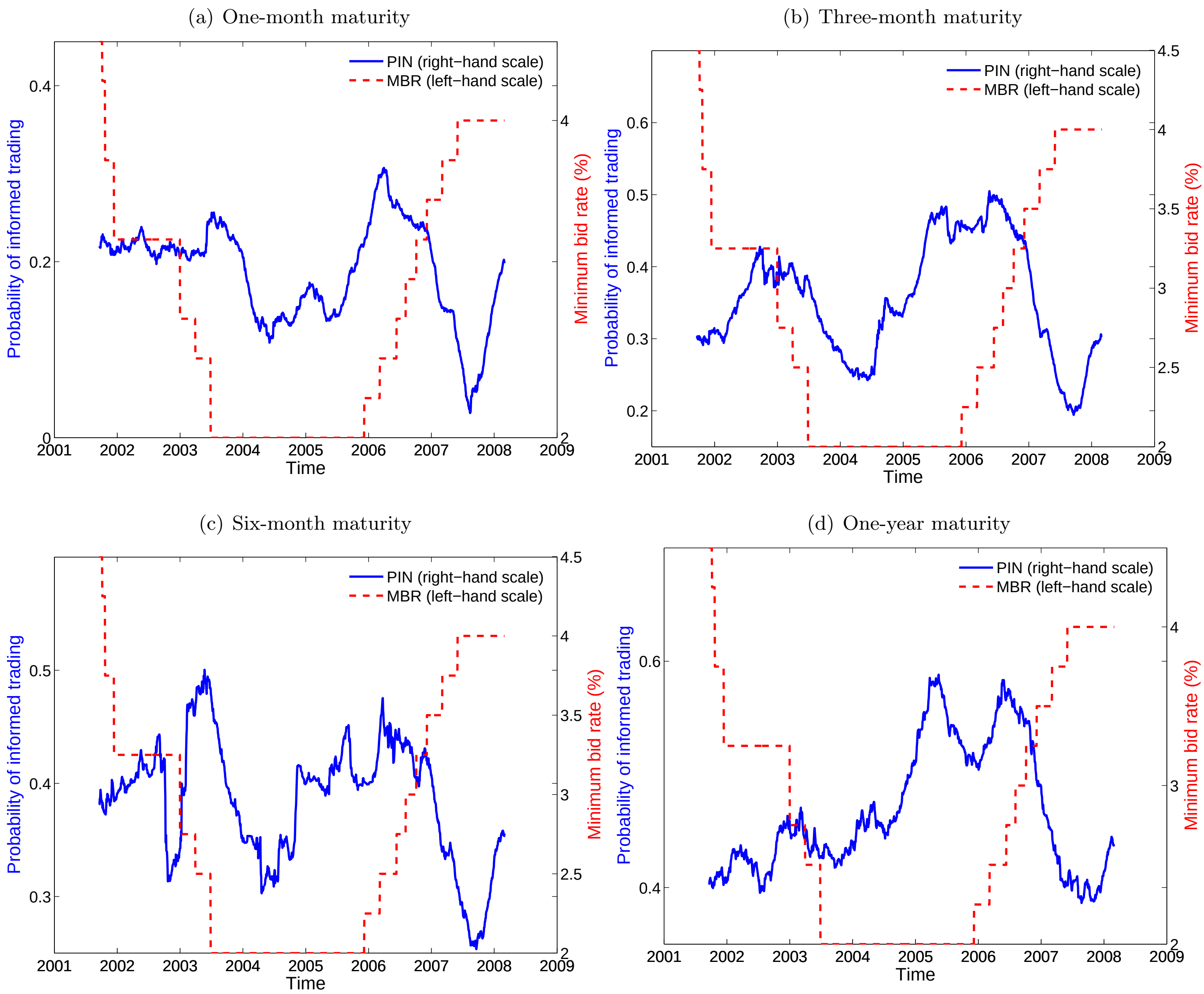
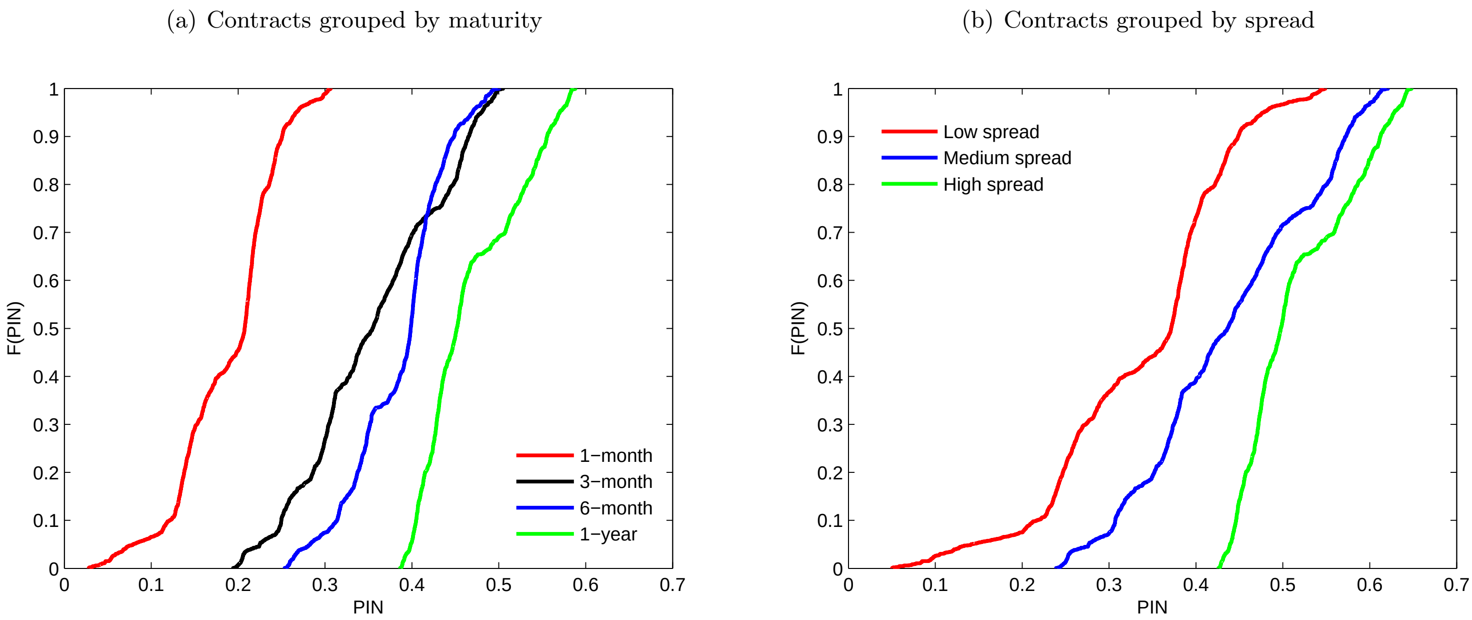


Figure 8: Rolling estimation of the PIN measures



Legend: These figures plot the PIN (in level) for each contract maturity and the policy cycle, represented by the minimum bid rate (in percentage points). The y-axis on the right-hand side reports the scale for the PINs. The scale for the minimum bid rate is the y-axis on the left-hand side of each figure.

Figure 9: Empirical distributions of the rolling PINs by groups



Legend: The vertical axis displays the cumulative probability while the horizontal axis represents the probability of information-based trading (PIN). Panel (a) displays the cumulative distribution of PIN for the three contract maturities. Panel (b) displays the cumulative distribution of the probability of PIN for low-, medium-, and high-spread groups.

Figure 10: Scatter plots of the PIN indicators and the realized volatilities

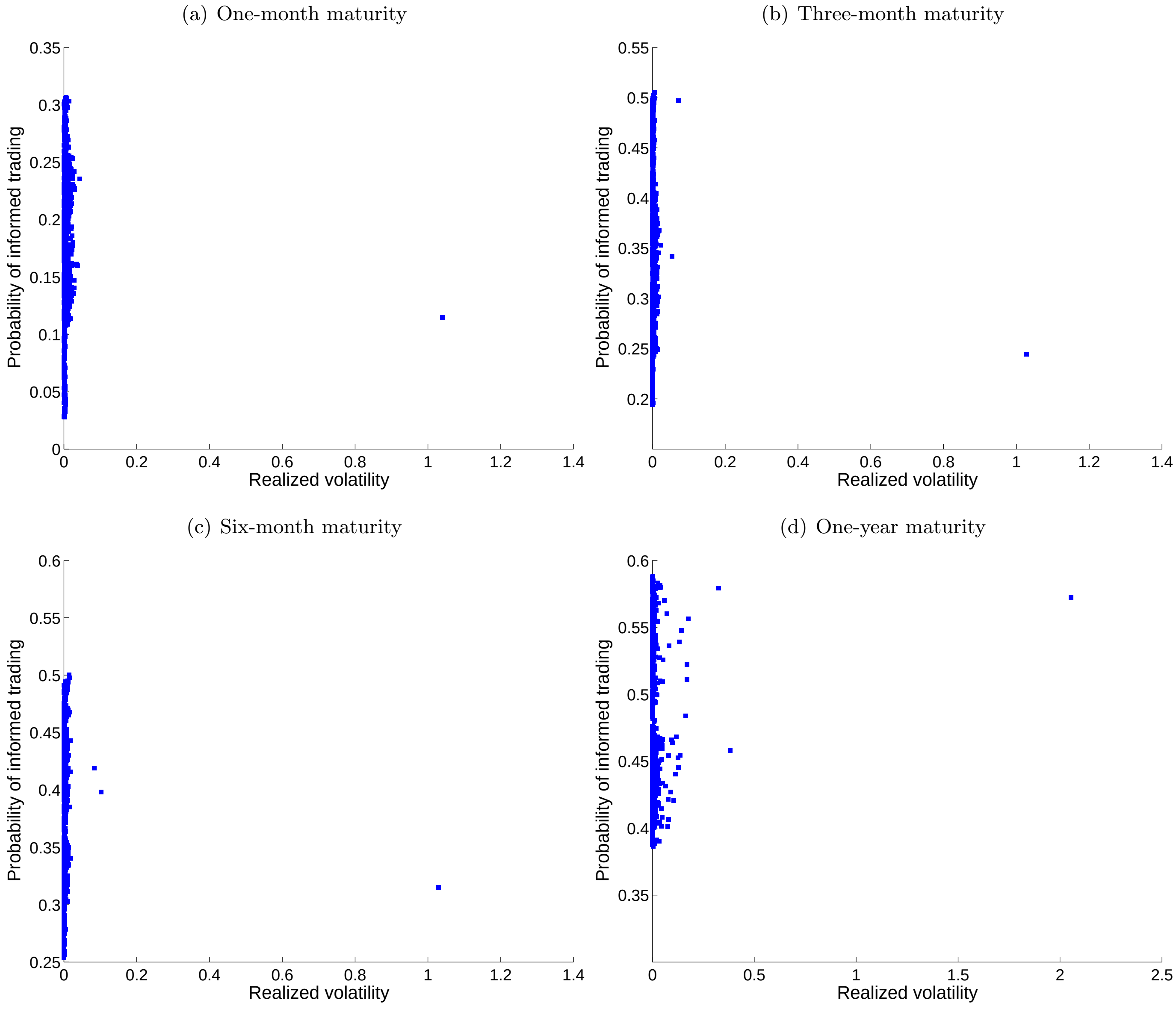


Table 1: Descriptive statistics of the distributions of inferred trades

	1-month	3-month	6-month	1-year
	Buy orders			
Mean	14.9374	15.8028	27.9666	31.1562
Std. dev.	8.6004	8.6736	9.0460	8.7358
Skewness	0.8207	0.4864	-0.5251	-0.9008
Kurtosis	3.3316	2.7327	3.4736	4.6380
	Sell orders			
Mean	15.0445	15.8929	28.0334	30.9315
Std. dev.	8.4460	8.6525	8.8256	8.4218
Skewness	0.7106	0.4865	-0.6734	-1.0571
Kurtosis	3.1142	2.6994	3.6306	4.9962
	No trade			
Mean	78.0181	76.3043	52	45.9122
Std. dev.	16.8176	17.0986	17.4136	16.5441
Skewness	-0.7528	-0.4694	0.7008	1.1543
Kurtosis	3.1634	2.6726	3.6628	5.2352

Table 2: Parameter estimates from full-sample estimation

Maturity	α	μ	δ	ϵ	Ψ	Log. lik.	PIN
1-month	0.2141	0.1636	0.5067	0.6093	06732	-142836.500	0.2430
	(0.0509)	(0.0710)	(0.0719)	(0.0790)			
3-month	0.2493	0.1522	0.4522	0.2656	0.3773	-147698.540	0.4033
	(0.0870)	(0.0115)	(0.0944)	(0.0318)			
6-month	0.3200	0.1374	0.5547	0.2047	0.3139	-193548.995	0.4376
	(0.1040)	(0.0216)	(0.1060)	(0.0484)			
1-year	0.3271	0.1236	0.6277	0.1629	0.2664	-199043.269	0.4640
	(0.0911)	(0.0390)	(0.1309)	(0.0916)			

Legend: Brackets indicate standard errors computed by evaluating the analytical Hessian at the global maximum.

Table 3: Descriptive statistics of the rolling PIN measures

	1-month	3-month	6-month	1-year
Mean	0.188	0.355	0.385	0.467
Std. dev.	0.053	0.080	0.056	0.042
Skewness	-0.408	-0.403	-0.498	-0.464
Kurtosis	2.673	1.990	2.875	2.425
	Contemporaneous correlation			
1-month	1			
3-month	0.739	1		
6-month	0.746	0.647	1	
1-year	0.674	0.485	0.920	1

Table 4: Unit root tests for the rolling PINs

	Constant	Constant and trend
(b) *1-month maturity*		
Test stat.	-2.17	-2.39
p-value	0.215	0.384
(c) *3-month maturity*		
Test stat.	-1.36	-1.34
p-value	0.602	0.875
(d) *6-month maturity*		
Test stat.	-1.82	-1.76
p-value	0.368	0.721
(e) *1-year maturity*		
Test stat.	-2.12	-1.92
p-value	0.233	0.640

Legend: This table reports test statistics and asymptotic p-values of the unit-root tests from Augmented Dickey Fuller regressions

Table 5: Kruskal-Wallis tests on rolling PIN

	Maturity	Spread
Test stat.	49.021	60.403
p-value	0.000	0.000

Legend: This table reports the statistics and the p-values of the Kruskal-Wallis test. This statistic is employed to test the null hypothesis that PIN values for all different groups are drawn from the same populations versus the alternative hypothesis that at least one of the populations is different from other populations. The money market contracts are divided into four groups according to the maturity (1, 3, 6 months, and 1 year). For the spread groups, I rank all the contracts based on daily average spreads, and divide them into low, medium, and high groups.

Table 6: Pairwise Wilcoxon rank-sum tests on rolling PIN

	Group 1 to 2	Group 1 to 3	Group 1 to 4	Group 2 to 3	Group 2 to 4	Group 3 to 4
Maturity	6.012 [0.000]	6.849 [0.000]	7.590 [0.000]	7.773 [0.000]	7.705 [0.000]	6.036 [0.000]
Spread	4.603 [0.000]	5.305 [0.000]	-	4.091 [0.000]	-	-

Legend: The Wilcoxon Rank-Sum statistic is employed to test the null hypothesis that two sample groups are drawn from identical populations against the alternative that one population has a higher PIN value. The money market contracts are divided into four groups according to the maturity (1, 3, 6 months, and 1 year). For the spread groups, I rank all the contracts based on daily average spreads, and divide them into low, medium, and high-spread groups. The table reports the test statistics and p-values (in brackets).

Table 7: The response of PINs to calendar effects

	1-month	3-month	6-month	1-year
$D_{6-\text{day},t}$	0.094	0.089	0.078	0.082
	[0.028]	[0.031]	[0.020]	[0.016]
$D_{\text{turmoi},t}$	0.059	0.021	0.070	0.094
	[0.011]	[0.009]	[0.002]	[0.021]
$D_{6-\text{day},t} \times D_{\text{turmoi},t}$	0.087	0.061	0.042	0.066
	[0.030]	[0.026]	[0.018]	[0.020]
$D_{\text{lastdays},t}$	0.110	0.111	0.104	0.120
	[0.031]	[0.044]	[0.042]	[0.059]
$D_{\text{turmoi},t}$	0.029	0.041	0.058	0.044
	[0.004]	[0.009]	[0.003]	[0.002]
$D_{\text{lastdays},t} \times D_{\text{turmoi},t}$	0.052	0.086	0.090	0.069
	[0.010]	[0.038]	[0.032]	[0.012]
$D_{\text{endm},t}$	0.110	0.111	0.102	0.104
	[0.020]	[0.023]	[0.017]	[0.018]
$D_{\text{turmoi},t}$	0.025	0.027	0.040	0.054
	[0.003]	[0.004]	[0.003]	[0.004]
$D_{\text{endm},t} \times D_{\text{turmoi},t}$	0.040	0.073	0.070	0.084
	[0.009]	[0.026]	[0.025]	[0.029]

Legend: All the regressions include a constant, whose coefficient estimates are not reported for brevity. This table reports the robust OLS estimates for the full sample. The standard errors are heteroskedasticity-consistent and adjusted for first-order autocorrelation.

Table 8: The relation between PINs and the type of open market operation

	1-month	3-month	6-month	1-year
$D_{\mathrm{mro},t}$	0.097	0.080	0.074	0.061
	[0.039]	[0.031]	[0.030]	[0.022]
$D_{\mathrm{turmoi},t}$	0.033	0.041	0.040	0.036
	[0.018]	[0.010]	[0.017]	[0.010]
$D_{\mathrm{mro},t} \times D_{\mathrm{turmoi},t}$	0.044	0.040	0.027	0.034
	[0.009]	[0.008]	[0.004]	[0.004]
$D_{\mathrm{fto},t}$	0.018	0.010	0.017	0.019
	[0.015]	[0.017]	[0.019]	[0.028]
$D_{\mathrm{turmoi},t}$	0.017	0.012	0.010	0.011
	[0.003]	[0.004]	[0.003]	[0.003]
$D_{\mathrm{fto},t} \times D_{\mathrm{turmoi},t}$	0.010	0.018	0.019	0.016
	[0.007]	[0.010]	[0.011]	[0.009]
$D_{\mathrm{ltro},t}$	0.059	0.080	0.096	0.083
	[0.022]	[0.035]	[0.040]	[0.031]
$D_{\mathrm{turmoi},t}$	0.013	0.038	0.049	0.027
	[0.004]	[0.013]	[0.007]	[0.005]
$D_{\mathrm{ltro},t} \times D_{\mathrm{turmoi},t}$	0.029	0.035	0.039	0.046
	[0.005]	[0.010]	[0.011]	[0.002]

Legend: All the regressions include a constant, whose coefficient estimates are not reported for brevity. This table reports the robust OLS estimates for the full sample. The standard errors are heteroskedasticity-consistent and adjusted for first-order autocorrelation.

Table 9: The relation between PINs and the type of liquidity supply

	1-month	3-month	6-month	1-year
$D_{\text{providing},t}$	0.085	0.074	0.057	0.072
	[0.030]	[0.029]	[0.017]	[0.025]
$D_{\text{turmoi},t}$	0.034	0.031	0.032	0.028
	[0.011]	[0.009]	[0.010]	[0.009]
$D_{\text{providing},t} \times D_{\text{turmoi},t}$	0.091	0.095	0.097	0.092
	[0.026]	[0.027]	[0.021]	[0.028]
$D_{\text{absorbing},t}$	0.045	0.027	0.024	−0.010
	[0.025]	[0.028]	[0.031]	[0.032]
$D_{\text{turmoi},t}$	0.031	0.040	0.041	0.041
	[0.010]	[0.007]	[0.012]	[0.008]
$D_{\text{absorbing},t} \times D_{\text{turmoi},t}$	0.017	0.019	0.005	0.018
	[0.012]	[0.012]	[0.002]	[0.013]
$D_{\text{supply}>\text{bench},t}$	0.094	0.096	0.092	0.090
	[0.021]	[0.022]	[0.021]	[0.025]
$D_{\text{turmoi},t}$	0.018	0.019	0.022	0.019
	[0.002]	[0.004]	[0.001]	[0.005]
$D_{\text{supply}>\text{bench},t} \times D_{\text{turmoi},t}$	0.081	0.074	0.081	0.077
	[0.016]	[0.014]	[0.018]	[0.020]
$D_{\text{supply}<\text{bench},t}$	0.105	0.107	0.101	0.092
	[0.026]	[0.021]	[0.016]	[0.019]
$D_{\text{turmoi},t}$	0.034	0.031	0.032	0.028
	[0.010]	[0.007]	[0.009]	[0.004]
$D_{\text{supply}<\text{bench},t} \times D_{\text{turmoi},t}$	0.085	0.087	0.091	0.080
	[0.014]	[0.012]	[0.021]	[0.020]

Legend: All the regressions include a constant, whose coefficient estimates are not reported for brevity. This table reports the robust OLS estimates for the full sample. The standard errors are heteroskedasticity-consistent and adjusted for first-order autocorrelation.

Table 10: Johansen cointegration tests for bivariate VAR models of rolling PIN measures

	λ-max test		Trace test	
	$r = 0/r = 1$	$r = 0/r = 2$	$r = 0/r > 0$	$r \leq 1/r > 1$
1-month and 3-month maturity	9.6	0.9	10.5	0.9
1-month and 6-month maturity	8.9	1.8	10.7	1.8
1-month and 1-year maturity	8.8	2.4	11.3	2.4
3-month and 6-month maturity	5.3	2.4	7.7	2.4
3-month and 1-year maturity	8.5	2.1	10.6	2.1
6-month and 1-year maturity	14.5	1.6	16.1	1.6

Legend: This table reports the test statistics for the cointegration tests of Johansen. The test is applied to pairs of PIN measures for different maturities of money market deposits. The models include an unconstrained constant and a time trend. The rank of the cointegrating vector is denoted by r. Stars denote significance at the 5% level.

Table 11: Bierens cointegration tests for bivariate VAR models of rolling PIN measures

	$r = 0/r = 1$	$r = 1/r = 2$
1-month and 3-month maturity	0.019	0.698
1-month and 6-month maturity	0.028	1.551
1-month and 1-year maturity	0.079	1.765
3-month and 6-month maturity	0.500	1.266
3-month and 1-year maturity	0.300	1.248
6-month and 1-year maturity	0.023	1.858

Legend: This table reports the test statistics for the nonparametric cointegration tests of Bierens. The test is applied to pairs of PIN measures for different maturities of money market deposits. The rank of the cointegrating vector is denoted by r. Stars denote significance at the 5% level. The results reported in this table were obtained using Easyreg.

Table 12: Relation between bid-ask spreads and PIN in a standard regression

	1-month	3-month	6-month	1-year
	Daily opening spread			
PIN_t	0.109	0.151	0.193	0.193
	[0.055]	[0.0609]	[0.100]	[(0.138]
RV_t	0.109	0.151	0.193	0.193
	[0.055]	[0.0609]	[0.100]	[(0.138]
$\text{D}_{\text{turmoil},t}$	0.021	0.024	0.024	0.027
	[0.008]	[0.007]	[0.006]	[0.006]
$\text{PIN}_t \times \text{D}_{\text{turmoil},t}$	0.052	0.055	0.057	0.056
	[0.011]	[0.010]	[0.009]	[0.013]
$\text{RV}_t \times \text{D}_{\text{turmoil},t}$	0.052	0.055	0.057	0.056
	[0.011]	[0.010]	[0.009]	[0.013]
R^2	0.015	0.016	0.008	0.012
	Daily median spread			
PIN_t	0.125	0.174	0.194	0.143
	[0.020]	[0.0227]	[0.037]	[0.051]
RV_t	0.109	0.151	0.193	0.193
	[0.055]	[0.0609]	[0.100]	[(0.138]
$\text{D}_{\text{turmoil},t}$	0.014	0.019	0.021	0.029
	[0.003]	[0.002]	[0.007]	[0.009]
$\text{PIN}_t \times \text{D}_{\text{turmoil},t}$	0.040	0.044	0.048	0.050
	[0.010]	[0.006]	[0.005]	[0.007]
$\text{RV}_t \times \text{D}_{\text{turmoil},t}$	0.052	0.055	0.057	0.056
	[0.011]	[0.010]	[0.009]	[0.013]
R^2	0.056	0.068	0.052	0.052
	Daily closing spread			
PIN_t	0.105	0.185	0.118	0.128
	[0.037]	[0.041]	[0.069]	[0.093]
RV_t	0.057	0.081	0.113	0.093
	[0.015]	[0.030]	[0.052]	[(0.028]
$\text{D}_{\text{turmoil},t}$	0.007	0.009	0.010	0.013
	[0.004]	[0.001]	[0.002]	[0.004]
$\text{PIN}_t \times \text{D}_{\text{turmoil},t}$	0.052	0.058	0.059	0.051
	[0.021]	[0.011]	[0.013]	[0.012]
$\text{RV}_t \times \text{D}_{\text{turmoil},t}$	0.022	0.015	0.009	0.012
	[0.010]	[0.004]	[0.002]	[0.003]
R^2	0.115	0.122	0.109	0.152

Legend: This table reports the estimates of the regression $\text{SPREAD}_t = c + b_1 (\text{PIN}_t) + b_2 (\text{RV}_t) + b_3 (\text{D}_{\text{turmoil},t}) + b_4 (\text{PIN}_t \times \text{D}_{\text{turmoil},t}) + b_5 (\text{RV}_t \times \text{D}_{\text{turmoil},t}) + e_t$. Brackets report standard errors. The standard errors are heteroskedasticity-consistent and adjusted for first-order autocorrelation. Estimated constants are not reported for brevity.

Table 13: Bid-ask spreads and PINs in a panel regression

	Opening spread	*Median spread*	*Closing spread*
$\mathrm{PIN}_{i,t}$	0.031	0.033	0.036
	[0.009]	[0.009	[0.011]
$\mathrm{RV}_{i,t}$	0.011	0.013	0.013
	[0.005]	[0.006	[0.004]
$\mathrm{D}_{\mathrm{turmoil},t}$	0.002	0.002	0.006
	[0.010]	[0.007]	[0.009]
$\mathrm{PIN}_{i,t} \times \mathrm{D}_{\mathrm{turmoil},t}$	0.009	0.010	0.011
	[0.002]	[0.003]	[0.002]
$\mathrm{RV}_{i,t} \times \mathrm{D}_{\mathrm{turmoil},t}$	0.010	0.012	0.014
	[0.004]	[0.003]	[0.004]
R^2	0.169	0.151	0.114

Legend: This table reports the estimates of the regression $\mathrm{SPREAD}_{i,t} = c + b_1\,(\mathrm{PIN}_{i,t}) + b_2\,(\mathrm{RV}_{i,t}) + b_3\,(\mathrm{D}_{\mathrm{turmoil},t}) + b_4\,(\mathrm{PIN}_{i,t} \times \mathrm{D}_{\mathrm{turmoil},t}) + b_5\,(\mathrm{RV}_{i,t} \times \mathrm{D}_{\mathrm{turmoil},t}) + e_{i,t}$. Brackets report standard errors. The standard errors are heteroskedasticity-consistent and adjusted for first-order autocorrelation. Estimated constants are not reported for brevity.

Table 14: Relation between returns and PIN in a standard regression

	1-month	3-month	6-month	1-year
PIN_t	0.099 [0.025]	0.107 [0.038]	0.104 [0.032]	0.113 [(0.038]
SPREAD_t	0.069 [0.015]	0.111 [0.041]	0.193 [0.100]	0.093 [(0.026]
RV_t	0.091 [0.029]	0.121 [0.036]	0.193 [0.100]	0.092 [(0.038]
$\text{D}_{\text{turmoil},t}$	0.081 [0.018]	0.024 [0.006]	0.024 [0.006]	0.077 [0.026]
$\text{PIN}_t \times \text{D}_{\text{turmoil},t}$	0.050 [0.011]	0.029 [0.010]	0.057 [0.009]	0.076 [0.028]
$\text{SPREAD}_t \times \text{D}_{\text{turmoil},t}$	0.072 [0.010]	0.035 [0.007]	0.057 [0.009]	0.066 [0.030]
$\text{RV}_t \times \text{D}_{\text{turmoil},t}$	0.072 [0.017]	0.019 [0.004]	0.057 [0.009]	0.076 [0.032]
R^2	0.154	0.131	0.150	0.142

Legend: This table reports the estimates of the regression model $r_t = c + b_1\,(\text{PIN}_t) + b_2\,(\text{SPREAD}_t) + b_3\,(\text{RV}_t) + b_4\,(\text{D}_{\text{turmoil},t}) + b_5\,(\text{PIN}_t \times \text{D}_{\text{turmoil},t}) + b_6\,(\text{SPREAD}_t \times \text{D}_{\text{turmoil},t}) + b_7\,(\text{RV}_t \times \text{D}_{\text{turmoil},t}) + e_t$. Brackets report standard errors. The standard errors are heteroskedasticity-consistent and adjusted for first-order autocorrelation. Estimated constants are not reported for brevity.

Table 15: Relation between returns and PIN in a panel regression

$\text{PIN}_{i,t}$	0.078 [0.024]
$\text{SPREAD}_{i,t}$	0.064 [0.013]
$\text{RV}_{i,t}$	0.055 [0.012]
$\text{D}_{\text{turmoil},t}$	0.032 [0.004]
$\text{PIN}_{i,t} \times \text{D}_{\text{turmoil},t}$	0.054 [0.011]
$\text{SPREAD}_{i,t} \times \text{D}_{\text{turmoil},t}$	0.029 [0.008]
$\text{RV}_{i,t} \times \text{D}_{\text{turmoil},t}$	0.023 [0.009]
R^2	0.152

Legend: This table reports the estimates of the panel regression $r_{i,t} = c + b_1(\text{PIN}_{i,t}) + b_2(\text{SPREAD}_{i,t}) + b_3(\text{RV}_{i,t}) + b_4(\text{D}_{\text{turmoil},t}) + b_5(\text{PIN}_{i,t} \times \text{D}_{\text{turmoil},t}) + b_6(\text{SPREAD}_{i,t} \times \text{D}_{\text{turmoil},t}) + b_7(\text{RV}_{i,t} \times \text{D}_{\text{turmoil},t}) + e_{i,t}$ Brackets report standard errors. The standard errors are heteroskedasticity-consistent and adjusted for first-order autocorrelation. Estimated constants are not reported for brevity.

Table 16: Out-of-sample predictability of PINs for the spreads in comparison with the random walk model

Statistic	**1-month maturity**			**3-month maturity**			**6-month maturity**			**1-year maturity**		
	Predictive horizons											
	1-day	**2-day**	**3-day**	**1-day**	**2-day**	**3-day**	**1-day**	**2-day**	**3-day**	**1-day**	**2-day**	**3-day**
LR	49.76***	26.79***	15.42***	7.61**	4.23	4.02	5.00*	6.27**	7.04**	7.29**	7.20**	7.18**
QLR	35.55***	31.74***	33.47***	39.37***	45.81***	47.78***	50.18***	49.96***	50.78***	53.37***	57.21***	54.32***
Exp-W	13.94***	12.02***	13.05***	16.16***	19.59***	20.26***	21.21***	21.09***	21.69***	23.27***	25.65***	24.30***
Nyblom	2.23***	2.07***	2.54***	3.34***	4.11***	4.31***	4.44***	4.17***	3.82***	3.77***	4.01***	3.76***
ENCNEWsp	-47.45**	-38.62**	-28.95*	-26.21**	-23.75**	-28.12*	-31.39**	-33.66*	-32.34**	-38.73**	-34.54**	-38.25**
ENCNEWre	-56.47**	-39.85**	-34.19*	-37.58*	-30.31**	-31.27**	-29.93**	-30.19**	-29.47**	-31.38**	-29.37**	-30.09**
ENCNEWro	-68.51**	-37.99**	-42.61*	-41.82**	-34.24*	-43.77**	-49.81**	-45.40**	-45.97*	-47.78*	-46.46*	-44.10*
Exp-W*	83.08***	61.74***	45.26***	32.71***	26.48***	23.40***	26.05***	28.36***	33.02***	36.18***	34.91***	31.84***
Mean-W*	99.78***	65.33***	45.96***	35.22***	31.33***	29.14***	29.32***	29.36***	29.46***	30.09***	29.67***	28.24***
Nyblom*	11.58***	5.49***	2.86	1.79	1.84	2.16	2.54	2.65	2.49	2.30	2.18	2.19
QLR*	173.90***	131.08***	97.59***	72.03***	60.11***	54.18***	59.76***	64.29***	73.31***	79.17***	75.99***	69.72***

Legend: This table reports the following test statistics and p-values. A series of tests for a one-time structural break: Andrews (1993) test, labeled QL, Andrews and Ploberger (1993) tests, labeled Exp-W and Mean-W, Nyblom (1989) test, labeled Nyblom. A series of optimal tests for parameter stability and no predictive content: the optimal Exponential Wald test, labeled Exp-W*, the optimal Mean Wald test, labeled Mean-W*, and the optimal Nyblom test, labeled Nyblom*. A series of tests for out-of-sample relative forecast comparisons: the test for forecasting comparisons for nested models discussed by Clark and McCracken (2001), labeled ENC-NEW. The latter tests are applied to rolling, recursive and fixed forecasting schemes, respectively labeled with the following subscripts: 'roll', 'rec', and 'fix'. ***rejection at the 1% level; **rejection at the 5% level; *rejection at the 10% level.

Table 17: Out-of-sample predictability of PINs for the returns in comparison with the random walk model

Statistic	**1-month maturity**			**3-month maturity**			**6-month maturity**			**1-year maturity**		
	Predictive horizons											
	1-day	**2-day**	**3-day**	**1-day**	**2-day**	**3-day**	**1-day**	**2-day**	**3-day**	**1-day**	**2-day**	**3-day**
LR	47.76***	26.79***	15.77***	7.61**	4.33	4.02	6.30*	6.37**	7.04**	7.74**	7.30**	7.15**
QLR	40.82***	34.74***	32.77***	32.37***	45.93***	47.75***	50.15***	47.96***	50.75***	48.37***	57.31***	54.32***
Exp-W	32.94***	32.02***	32.19***	36.16***	32.59***	26.36***	24.31***	24.09***	24.69***	40.37***	25.65***	24.30***
Nyblom	2.33***	2.07***	2.54***	2.34***	4.19***	4.70***	4.74***	4.17***	2.78***	2.77***	4.01***	2.76***
ENCNEWsp	-47.75**	-40.62**	-25.95*	-26.31**	-40.75**	-25.12*	-34.74**	-32.66**	-32.34**	-40.73**	-34.54**	-40.70**
ENCNEWre	-56.77**	-32.82**	-34.19*	-37.82*	-30.70**	-34.37**	-40.93**	-30.19**	-40.77**	-34.70**	-40.37**	-30.09**
ENCNEWro	-65.93**	-37.38**	-47.61*	-44.78**	-34.34**	-47.77**	-47.93**	-45.70**	-45.97	-47.75	-46.76	-44.10
Exp-W*	48.19***	64.74***	45.36***	32.71***	26.75***	40.70***	26.19***	25.36	32.02	36.15***	34.91***	34.54***
Mean-W*	92.75***	65.33***	45.96***	40.70***	34.33***	40.14***	40.32***	40.36***	40.76***	30.09***	40.67***	25.34***
Nyblom*	14.82***	5.79***	2.56	4.79	4.54	2.16	2.54	2.65	2.79	2.30	2.15	2.19
QLR*	62.90***	54.19***	97.59***	72.03***	60.19***	54.15***	48.76***	64.74***	72.70***	72.17***	75.38***	62.72***

Legend: This table reports the following test statistics and p-values. A series of tests for a one-time structural break: Andrews (1993) test, labeled QL, Andrews and Ploberger (1993) tests, labeled Exp-W and Mean-W, Nyblom (1989) test, labeled Nyblom. A series of optimal tests for parameter stability and no predictive content: the optimal Exponential Wald test, labeled Exp-W*, the optimal Mean Wald test, labeled Mean-W*, and the optimal Nyblom test, labeled Nyblom*. A series of tests for out-of-sample relative forecast comparisons: the test for forecasting comparisons for nested models discussed by Clark and McCracken (2001), labeled ENC-NEW. The latter tests are applied to rolling, recursive and fixed forecasting schemes, respectively labeled with the following subscripts: 'roll', 'rec', and 'fix'. ***rejection at the 1% level; **rejection at the 5% level; *rejection at the 10% level.

Table 18: Out-of-sample forecast comparisons between extended models with the test of Clark and McCracken (2001)

Predictive horizons		
1-day	2-day	3-day
Panel (a): Unrestricted: $\Delta\text{SPREAD}_{t+h} = c + b_1(\Delta\text{SPREAD}_t) + b_2(\Delta\text{PIN}_t) + b_3\text{RV}_t + e_t$ Restricted: $\Delta\text{SPREAD}_{t+h} = c + b_2(\Delta\text{PIN}_t) + e_t$		
-5.25***	-6.09***	-5.96***
Panel (b): Unrestricted: $r_{t+h} = c + b_1\text{r}_t + b_2(\Delta\text{SPREAD}_t) + b_3(\Delta\text{PIN}_t) + b_4\text{RV}_t + e_t$ Restricted: $r_{t+h} = c + b_3(\Delta\text{PIN}_t) + e_t$		
-7.76***	-7.79***	-9.42***
Panel (c): Unrestricted: $\Delta\text{SPREAD}_{t+h} = c + b_1(\Delta\text{SPREAD}_t) + b_2(\Delta\text{PIN}_t) + b_3\text{RV}_t + e_t$ Restricted: $\Delta\text{SPREAD}_{t+h} = c + b_1(\Delta\text{SPREAD}_t) + b_3\text{RV}_t + e_t$		
-1.25***	-1.09**	-1.96***
Panel (d): Unrestricted: $r_{t+h} = c + b_1\text{r}_t + b_2(\Delta\text{SPREAD}_t) + b_3(\Delta\text{PIN}_t) + b_4\text{RV}_t + e_t$ Restricted: $r_{t+h} = c + b_1\text{r}_t + b_2(\Delta\text{SPREAD}_t) + b_4\text{RV}_t + e_t$		
-1.76***	-1.79***	-0.42

Legend: This table reports ENCNEW test statistics for rolling samples. These statistics are the scaled differences of mean squared forecast errors between the unrestricted and the restricted model. Negative values imply that the unrestricted model forecasts better than the restricted. The null hypothesis is that the restricted predicts better, against the alternative hypothesis that the unrestricted model delivers predictive gains. The critical values are reported by Clark and McCracken (2001). ***rejection at the 1% level; **rejection at the 5% level; *rejection at the 10% level.