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Intraday volatility, trading volume and trading intensity in the interbank market e-MID

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Intraday volatility, trading volume and trading intensity in the interbank market e-MID

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Abstract

We apply a multivariate multiplicative error model (MMEM) and investigate effects in the simultaneous processes of high-frequency return volatilities, trading volume, and trading intensities on the Italian Electronic Interbank Credit Market (e-MID). Analysing five minutes data from the Italian interbank market (e-MID), we found that volatilities, volumes and trading intensities on electronic Interbank Credit Market share strong causal relationship resulting in highly significant estimates of MMEM. In addition, we run several estimations to observe a change in the market behaviour of the e-MID during the last financial crisis. The main results of our study are the usability of high-frequency data models for the analysis of interbank credit market data. Moreover, we find out that changes in the market behaviour occur during the crisis. Before the financial crises, liquidity variables have a negative influence on the volatility, in contrast to the time period after the outbreak of the financial turmoil. To our best knowledge, our paper presents the first empirical application of MMEM to an interbank credit market.

Keywords: Multiplicative error models, interbank markets, e-MID, interstate volatility, trading intensity, intraday trading process, high-frequency financial data

JEL Classification: C15, C32, C52, C55, C58, E43, G01, G12

1. Introduction

In the light of the increasing availability of high-frequency financial data, the empirical analysis of trading behaviour and the modelling of trading processes has become a major subject in financial econometrics. In several empirical studies, a strong contemporaneous relation between daily aggregated volume and volatility was documented for mostly all financial markets. This observation is in line with the mixture-of-distribution hypothesis (MDH) pioneered by Clark (1973), which relies on central limit arguments based on the assumption that daily returns consist of the sum of intradaily (logarithmic) price changes associated with intraday equilibria. A numerous further studies also investigate this relation for smaller intra-daily time intervals. Referred to these studies, the first aim of this work is to analyse the interbank credit market for the relationships given above. In addition,

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further variables of interest are price volatilities, trading volume, trading intensities, bid-ask spreads and market depth as displayed by an open limit order book.

These variables are positive-valued and persistently clustered over time, which is an important characteristic for high-frequency financial data models. To capture the stochastic attributes of positive-valued autoregressive processes, multiplicative error models (MEM) have been introduced. According to this, the second aim of this work is to verify if these high-frequency models are also applicable to aggregated and to model the dynamic of intraday interbank market data.

The idea of modelling a positive-valued process based on the product of positive-valued innovation terms and an observation-driven (or parameter driven) dynamic function is a common application in financial econometrics. The basic models are the autoregressive conditional heteroscedasticity (ARCH) model introduced by Engle (1982) or the stochastic volatility (SV) model proposed by Taylor (1982).

Engle and Russell (1997, 1998) introduced the autoregressive conditional duration (ACD) model to model autoregressive duration processes in terms of a multiplicative error process and a GARCH-type parameterization of the dependent duration mean for financial data. The term MEM was firstly introduced by Engle (2002). In his work, he approached the ("standard") MEM as a general framework to model positive-valued dynamic processes. Manganelli (2005) extended this work and proposed a multivariate MEM to model jointly high-frequency volatilities, trading volume and trading intensities. Hautsch (2007) generalizes the basic MEM structure by adding a common latent dynamic factor serving as a subordinated process driving the used components. This model combines features of a GARCH type model and an SV type model and is called stochastic MEM. Engle and Gallo (2006) also deploy several MEM specifications to model jointly different volatility indicators like absolute returns, daily range, and realized volatility. Cipollini et al. (2007) extend the MEM by a copula specification to capture contemporaneous relationships between the used variables.

Because of the growing importance of MEMs for the modelling of high-frequency trading processes, liquidity dynamics, volatility and other market processes, we will present an application of the MEM to model the multivariate dynamics of volatility, trade sizes and trading intensities based on transaction data from the Italian interbank market (e-MID).

There are already several studies on the interbank market, in particular on the e-MID, with different research topics. Gabbi et al. (2012) examine the market microstructure, the behaviour of the banks and the interbank spreads for a period from 1999 to 2009 on daily aggregated data. The same time period is object of the work of Raddant (2012) who focused on the trade flow, the absolute volume and the preferred lending relationships in the market. In addition, Politi et al. (2010) give an overview on the market using simple statistics and introduce some variable computation for the time before and during the financial crisis.

A second object of the studies on the market is the network analysis executed by Iori et al. (2007, 2008) or Mistrulli (2011). Their findings show that the Italian interbank network is divided in two groups - one consisting of Italian banks and another one composed of foreign banks, and has two main junctures represented by huge Italian banks.

The behaviour of the interest rate and the micro- and macroeconomic determinants of the interest rate is examined by Kapar et al. (2012), Angelini et al. (2009) and Gabrielli (2010). They use

transaction data from overnight loans as well as longer maturities. Baglioni and Montecini (2008b) construct a hypothetic market for one hour interbank loans to compute “intraday price of money” for the Italian interbank market.

The volume represents another main topic of the studies on the Italian interbank market. Porzio et al. (2010) use an autoregressive model with multiple predictors to forecast the traded volume of the market. The liquidity distribution during the crisis was investigated by Vento (2010). Brunetti et al. (2009) combine their study on the volume with the investigation of the effect of the Central Banks decisions on the market. Fricke (2012) also does a combined work on the volume of the market and the trading strategy of the market participants. All these studies find constant decrease of the market volume during the crisis, which leads to market break down.

However, to our best knowledge, there is no work on the analysing the microstructure of an interbank credit market applying multivariate multiplicative error models. Hence, the aim of our paper is to close this gap and to present first results in the context of the framework of multiplicative multivariate error models for an interbank credit market.

The paper is organized as follows: Section 2 presents the major principles of the MEM and will also introduce a multivariate specification of a MEM. The used data and the mechanism of the Italian interbank market are described in section 3. Section 4 gives an overview on the variable computation, the used model specifications and the estimation results. Finally, Section 5 concludes.

2. Multiplicative multivariate error models

In this section of the study, we give an overview about the econometric model and we present the model specification used for our analysis.

The univariate MEM

Let $\{Y_t\}, t = 1, \dots, T$ denote a non-negative random variable. Then, the univariate multiplicative error model (MEM) for Y_t is given by

$$(1) \quad Y_t = \mu_t \varepsilon_t$$

$$(2) \quad \varepsilon_t | \mathcal{F}_{t-1} \sim i. i. d. D(1, \delta^2)$$

where \mathcal{F}_t denotes the information set up to t , μ_t is a non-negative conditionally deterministic process given \mathcal{F}_{t-1} and ε_t is a unit mean, i.i.d. variate process defined on non-negative support with variance δ^2 . Then the following shall apply:

$$(3) \quad E[Y_t | \mathcal{F}_{t-1}] \stackrel{\text{def}}{=} \mu_t$$

$$(4) \quad \text{Var}[Y_t | \mathcal{F}_{t-1}] = \delta^2 \mu_t^2$$

The major idea of the MEM is to parameterize the conditional mean μ_t in terms of a function of the information set \mathcal{F}_{t-1} and parameters θ . The basic linear MEM (p, q) than can be written as,

$$(5) \quad \mu_t = \omega + \sum_{j=1}^p \alpha_j Y_{t-j} + \sum_{j=1}^q \beta_j \mu_{t-j}$$

with $\omega > 0$, $\alpha_j \geq 0$ and $\beta_j \geq 0$.

This basic linear MEM was introduced by Manganelli (2005) and Engle (2002). For a closer look at the specifications and variations of the model of our interest, see Hautsch (2007), Hautsch and Jeleskovich (2008) and Engle et al. (2012).

The linear MEM specification is extended to an often used logarithmic specification of a MEM. This specification ensures the positivity of μ_t without implying parameter constraints. This is especially important whenever the model is augmented by explanatory variables or when the model has to accommodate negative cross correlations or autocorrelations in a multivariate setting. Two versions of the logarithmic MEM, already introduced by Bauwens and Giot (2000), are given (with $p = q = 1$) by

$$(6) \quad \log \mu_t = \omega + \alpha g(\varepsilon_{t-1}) + \beta \log \mu_{t-1}$$

where $g(\cdot)$ is given either by $g(\varepsilon_{t-1}) = \varepsilon_{t-1}$ or $g(\varepsilon_{t-1}) = \log \varepsilon_{t-1}$. The process is covariance stationary if $\beta < 1$, $E[\varepsilon_t \exp\{\alpha g(\varepsilon_t)\}] < \infty$ and $E[\varepsilon_t \exp\{2\alpha g(\varepsilon_t)\}] < \infty$. For more details, see Bauwens and Giot (2000).

The multivariate vector MEM

For a k -dimensional positive-valued time series, denoted by $\{Y_t\}$, $t=1\dots T$, with $Y_t \stackrel{\text{def}}{=} (Y_t^{(1)}, \dots, Y_t^{(k)})$, the vector MEM (VMEM) for Y_t is defined by

$$(7) \quad Y_t = \mu_t \odot \varepsilon_t = \text{diag}(\mu_t) \varepsilon_t$$

where \odot denotes the Hadamard product (element-wise multiplication) and ε_t is a k -dimensional vector of reciprocal and serially innovation processes where the j -th element is given by

$$(8) \quad \varepsilon_t^{(j)} | \mathcal{F}_{t-1} \sim i.i.d. D(1, \delta_j^2), \quad j = 1, \dots, k.$$

The extension of the linear MEM proposed by Manganelli (2005) and Engle (2002) is then given by

$$(9) \quad \mu_t = \omega + A_0 Y_t + \sum_{j=1}^p A_j Y_{t-j} + \sum_{j=1}^q B_j \mu_{t-j}$$

where ω is a $(k \times 1)$ vector and A_0 , A_j and B_j are $(k \times k)$ parameter matrices. The A_0 matrix captures the relationships between the elements of Y_t and only its upper triangular elements are non-zero.

This structure implies that $Y_t^{(i)}$ is predetermined for all variables $Y_t^{(j)}$ with $j < i$. So $Y_t^{(i)}$ is conditionally i.i.d. given $\{Y_t^{(j)}, \mathcal{F}_{t-1}\}$ for $j < i$. With this specification the relationship between the variables is taken into account without requiring multivariate distributions for ε_t and eases the estimation of the

model. The ordering of the variables in the Y_t matrix is typically chosen in accordance with the research objective or follows economic reasons.

In correspondence to the univariate logarithmic MEM, we obtain a logarithmic VMEM specification by

$$(10) \quad \log \mu_t = \omega + A_0 \log Y_t + \sum_{j=1}^p A_j g(\varepsilon_{t-j}) + \sum_{j=1}^q B_j \log(\varepsilon_{t-j})$$

where $g(\varepsilon_{t-j}) = \varepsilon_{t-j}$ or $g(\varepsilon_{t-j}) = \log \varepsilon_{t-j}$, respectively.

3. Data and e-MID

In this section, we explain the main characteristics of the e-MID interbank market and the dataset we used in this study. We also describe the computation of the used variables and show some statistical facts and descriptive statistics.

e-MID

The e-MID interbank market is a full automatic platform for interbank loan, managed by the e-MID company (Italy) and supervised by the Bank of Italy. Credit institutions and investment companies can participate in the market system if their total asset size is about 10 Million US-Dollar (or its equivalent in another currency) or 300 million Euros (or equivalent in another currency).

One main difference to other interbank markets is that it is almost fully transparent to all participants. Buy and sell proposals appear on the market platform together with the identity (bank-ID) of the market member. In sell transactions, the money flows from the aggressor bank to the quoter bank. In this case, the quoter bank is borrowing money and the aggressor is lending money. In buy transactions, the money flows from the quoter bank to the aggressor bank which indicates that the aggressor is borrowing and the quoter bank is lending. The aggressor bank is the bank placing the order in the market or the bank which actively chooses an existing order. The trading takes place during the time period from 8:00 a.m. to 6:00 p.m. ECT.

The e-MID market does not offset any counter party risk because the participants always know the opponent by its bank-ID. Also the search costs for all platform participants are identical. In the market, each bank can actively choose any counter party present in the order book to start a trade. The two parties than can negotiate about the trade, change the volume or price (credit rate) or deny the transaction.

This transparency in the market can bring a disadvantage during a financial crisis. If there is a high uncertainty in financial markets and banks also give importance to reputation game, the banks avoid trading in such transparent markets. Given this behaviour, the transaction volume and the number of participants in the market consequently decrease during the financial crisis.¹

¹ For further details about e-MID, see e.g. Baglioni and Monticini (2008b) or Gabbi et al. (2012).

Dataset

We use a dataset which includes all transactions in the e-MID interbank market from 1.10.2005 to 31.03.2010.² For each transaction we have information about the date, the time of the trade, the quantity, the interest rate, the type of the transaction (sell or buy) and the Bank-ID of the quoter and the aggressor. Table 1 shows an example of the transaction data.

In this study we concentrate on the overnight (ON) and the overnight large (ONL) transactions, because these transactions cover more than 90% of the total transaction volume in the market. The overnight large trades have a size over 100 Million euros. We also compute the volume-weighted mean rate as

$$(11) \quad \bar{r}_w^t = \frac{\sum_{i=1}^{N_t} r_i v_i}{\sum_{i=1}^{N_t} v_i}$$

where N_t is the number of transactions in an interval and v_i and r_i represent the volume and the rate of the i^{th} transaction in the interval. This computation is necessary, because we only have information about the executed orders and information about the whole order book of the market.

According to Politi (2010), Gabrieli (2011), Masi et al. (2006), Gaspar et al. (2007), Iori et al. (2007), Iori and Precup (2007), Iori et al. (2008), Gabbi et al. (2012) and Raddant (2012), who use a similar dataset for their investigations on the Italian interbank market, these computed rate (and also its volatility) can be used in statistic models or for statistical analyses. In addition, Brunetti (2009) and Baglioni and Monticini (2008 a,b) used the data for intra-daily analyses of the interest rate, intraday volatility and intraday market behaviour.

To investigate a change in the market behaviour before, during and after the crisis we divide the total data set in four sub periods. For the length of each period we orientate ourselves by the definition of Gabbi et al. (2012), Gabrieli (2011) and Politi et al. (2010) for their analyses. In addition, we split the third period into two sub periods, because we recognise that the preferred classification of the former studies accord to the EZB key rate (RPS³ and DEP⁴) decisions. So we split the third period by 13. March 2009 (latest change of the RPS) to see if there are any changes in the market behaviour based on the rate decisions of the EZB. Figure 1 shows the e-MID rate, the **RPS** and the **DEP**.

The first analysed period reaches from 1.10.2005 to 8.8.2007 (P1), the second period reaches from 9.8.2007 to 14.9.2008 (P2), the third period reaches from 15.9.2008 to 12.5.2009 (P3) and the fourth period reaches from 13.5.2009 to 31.3.2010 (P4). According to the mentioned literature, the two main events of the financial crisis are the first intervention of the ECB on 9.8.2007 and the collapse of Lehman Brothers in the USA on 15.9.2008. In addition we see the 13.5.2009 as an important event in

² We use the German date notation (dd.mm.jjjj).

³ Main refinancing facility operations (**RPS**) are regular liquidity-providing reverse transactions with a frequency and maturity of one week. They are executed by the NCBs on the basis of standard tenders and according to a pre-specified calendar. The main refinancing operations play a pivotal role in fulfilling the aims of the Euro system's open market operations and normally provide the bulk of refinancing to the financial sector.

⁴ Deposit facility rate (**DEP**): counterparties can use the deposit facility to make overnight deposits with the NCBs. The interest rate on the deposit facility normally provides a floor for the overnight market interest rate.

the European interbank markets, because it is the date of the latest reduction of the key interest rates by the ECB.

4. Main results

In this section, we will describe the variables and their computations, show some descriptive statistics of the Italian interbank market and illustrate an application of the VMEM to model jointly return volatilities, average trade sizes and the number of trades for intra-day trading in the interbank market.

Variables and descriptive statistics

Based on the early findings of Karpoff (1987) and Harris (1994) and in line with Hautsch (2007) and Hautsch and Jeleskovic (2008), the main purpose of our study is to analyse the influence of the volume and the trade intensity on the volatility in the interbank market. We want to examine if there is a similar link between these variables as the authors above have figured out for other financial markets. For our analysis we use five minute intervals for aggregate the variables like Hautsch (2007) uses for his (S)MEM study on US Blue Chips or like Brunetti et al. (2009) for their study on the News Effect on the e-MID market. This aggregation helps to reduce the complexity of the model and allows us to compute usable data even in periods with very low trading intensity. For applications of MEMs to irregularly spaced data, see Manganelli (2005) or Engle (2000). Table 2 shows the descriptive statistics of the variables for each period (including all zero value intervals).

In order to reduce the impact of opening and closure effects, we decide to use only the observations from 9:00 a.m. to 5:30 p.m., because in the opening and closing hours the market participants typically analyse the information of the former day to plan their activities and so the market volume and market activity is very low and not representative for the relationships between the variables.⁵

A typical feature of high-frequency intraday data is the strong influence of intraday seasonality, which is shown by several empirical studies. For closer look see Bauwens and Giot (2001) or Hautsch (2004). According to empirical findings from other markets (for example, Hautsch and Jeleskovic (2008)), we observe that the liquidity demand (volume per trade and trade intensity) follows a U-shape pattern with a period of low trading activity around noon. Like Hautsch and Jeleskovic (2008), we also observe the highest volatility after the opening of the market and before the closure, which is an indication of information processing during the first minutes of trading similar to the most other financial markets.

One possibility to face intraday seasonality is to augment the specification of μ_t by appropriate regressors. An alternative way is to adjust to seasonality in a first step. For this possibility the effect of a pre-adjustment on the final parameter estimates is controversially discussed in the literature (see Veredas et al. (2001)). Like most empirical studies prefer the two-stage method since it reduces the model complexity and the number of parameters to be estimated in the final step, we also follow this proceed in pre-adjust the variables. For the seasonal adjustment we use a moving average (MA)

⁵ We based our decision on the work of Brunetti (2009) and Baglioni and Montichini (2008b). Brunetti identifies a time interval from 8:30 a.m. to 5:00 p.m. as representative in his study of Central Bank intervention effects. Baglioni and Montichini identify the time interval from 9:00 a.m. to 18:00 p.m. as representative in their study of the hypothetical intraday loan market.

with the total length of 97 intervals to compute the seasonal factor of each interval on every day.⁶ In the next step we compute the average of the seasonal components for each interval over each sub period. Then, we divide the variable by the seasonal component of the corresponding interval to get the adjusted variables. At last, we divide the variable by the seasonal factor to get an estimate for the seasonal component of each interval.⁷ The resulting seasonality patterns are shown in Figure 2 to Figure 5.

In the first two periods the main volatility occurs at the end of the trading time. In the third period the volatility decreases in the evening hours 4 p.m. to 6 p.m. and increases again in the morning hours and increases in the morning hours 8 a.m. to 9 a.m. However, as a contrast, in the fourth period the main volatility occurs in the morning hours, the opening of the market. The volatility in the evening hours is still present in period four (and higher compared to the previous periods). The intraday seasonality of the volume variable has the typical U shape with huge orders in the morning and evening hours. A small spike is also visible around the lunch time (1 p.m. to 3 p.m.), which represents a period with only a few but huge orders in the market. In period one, two and four the mean volume drops rapidly for the last hour of trading. The intraday seasonality pattern for the number of trades per five minute interval also shows that the main trading activity takes place between 9:30 a.m. to 4:30 p.m., with a dip around noon. The pattern is similar for all periods.

For the estimation purpose we use the autocorrelation and cross correlation of the computed variables as indication for the ordering of the variables. All variables are significantly auto correlated at lag one for all four periods, except the volume variable in period four, which is highest auto correlated at lag four. The cross correlation for all variables is highest (or lowest) at lag zero, except for the cross correlation of the squared returns and the number of trades in the third period. The two variables are significantly cross correlated at lag 13, which is an indication of the change of the trading behaviour in the crisis period.⁸ Due to the autocorrelations and cross correlations of the variables and in respect to the subject of this work, we chose the volatility variable (squared log returns as the dependent variable⁹). Furthermore, we assume the volume variable depends on the number of trades per five minute interval.

Like Hautsch (2007) and Hautsch and Jeleskovic (2008) for the process of squared returns, $Y_t^{(1)} = r_t^2$, we assume $Y_t^{(1)} | Y_t^{(2)}, Y_t^{(3)}, F_{t-1} \sim N(0, \mu_t^{(1)})$ and for $Y_t^{(j)}$, $j \in \{2, 3\}$, we assume $Y_t^{(j)} | Y_t^{(j+1)}, \dots, Y_t^{(3)}, F_{t-1} \sim Exp(\mu_t^{(j)})$. Though it is well-known that both the normal and the exponential distribution are not flexible enough to capture the distributional properties of high-frequency trading processes, they allow for a QML estimation of the model, but the trading size in the most cases is less than 100 Million (and it is only possible to trade a volume which is multiple of five million). The number of trades in the most cases is also between zero and 20 with a maximum of 28 per interval.

⁶ Due to 97 intervals per day.

⁷ Hautsch (2007) uses cubic spline function for seasonal adjustment. For our case of equal-length time intervals the both methods lead to the same results.

⁸ The higher lag in the cross correlation of the volatility variable and the number of trades indicates a low level of market activity in the third period combined with still remaining high volatility.

⁹ Depends on volume and number of trades.

Because the VMEM is not tractable with non-positive valued variables, we remove all the intervals with zero values for at least one of the three variables and normalize the variables dividing them by their mean value.

Finally we estimate a three-dimensional Log-VMEM for squared log returns, trade sizes and the number of trades by their corresponding seasonality components. For simplicity and to keep the model tractable, we restrict our analysis to a specification of the order $p = q = 1$ and fully parameterized matrix A_1 and diagonal B_1 matrix. The innovation term is chosen as $g(\varepsilon_t) = \varepsilon_t$.

Estimation results for multivariate VMEM

Table 3 shows the estimation results for the four periods and Table 4 shows the descriptive statistics of the used variables and the VMEM residuals based on the specification explained above.

We can summarize the following major findings:

First, we achieve significant parameter estimates, and thus, we can state that there is the significant and relevant interdependency between all variables during all periods. Confirming the descriptive statistics, volatility is positively correlated with liquidity demand and liquidity supply. Periods of active trading driven by high volumes and high trading intensities is accompanied by high volatility.

Second, as indicated by the diagonal elements in A_1 and the elements in B_1 , all trading components are strongly positively auto correlated but are not persistent in equal measure and in each period. The persistence for trade sizes and trading intensities is higher than for volatility in the first two periods. In the last two periods the persistence for trade sizes and trading intensities is lower than for volatility. This is an impact of the consequently decreasing liquidity supply (volume and market participants) during the crisis and is in line with the findings of Brunetti (2009), who investigates a crowding out effect on the interbank market by rising ECB activities.

Third, trade sizes are significantly positively driven by past trading intensities during all periods. This finding indicates that a higher speed of trading tends to raise trade sizes over time. Hence, market participants observing a low liquidity supply raise the trade sizes but trade less. A possible explanation for this finding is that the market participants demand higher loan sizes to have an amortization reserve to eventually pay back outstanding loans, even if the interbank market is short on liquidity supply.

Fourth, the influence of the liquidity variables on the volatility changes during the crisis. In the first period both liquidity variables have a negative influence on the volatility. From the second to the fourth period the trading size has positive influence on the volatility. The trading intensity is still negatively correlated with the volatility during the second and third period, but in the fourth period the correlation also becomes positive. This fact is a clear evidence for a change in the behaviour of the market participants during the crisis. A low number of trades in an interval and a higher average volume per trade lead, per definition of the volume weighted mean rate, to a rising volatility in the market in period two and three.

Fifth, as shown by the summary statistics of the MEM residuals, the model captures a substantial part of the serial dependence in the data. This is indicated by a significant reduction of the corresponding Ljung-Box statistics, but for some processes, there is still significant remaining serial dependence in the residuals. The Ljung-Box statistics also indicate the presence of a strong serial

dependence in volatilities and the two liquidity variables, which is a clear indication for the well-known clustering structures in the trading processes.

5. Conclusion

In summary, we find strong dynamic interdependencies and causalities between high-frequency volatility, liquidity supply and liquidity demand on e-MID. Such results might serve as valuable input for trading strategies and (automated) trading algorithms. The results are also useful for political and financial decisions as they could help indicating and estimating the possible effects on the interbank markets and in addition, they could enhance the timing of macroeconomic driven decisions. By using econometric models for high-frequency data like the MEM on interbank markets (with a macroeconomic nature), the direction of the required effects can be assumed and the behaviour of the market members may be more foreseeable in this case.

We also show that models for high-frequency financial data can also be used for the analysis of the interbank market. In this case it may be recommendable to compute tractable variables which correspond to the normally used variables like in other financial markets (for example computing the interest rates without whole order book information).

In addition, we show that the already known influence from the liquidity variables on the volatility in the market also exists in the interbank market, but the behaviour of the market participants is different during the financial crises. This change in the trading behaviour may be a signal for some shortcomings of the e-MID and a market failure or market inefficiency during and after the financial crisis, which is already observed by other authors (e.g. Porzio et al. (2009)).

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Appendix

Market	Duration	Date	Time	Rate	Amount	StartDate	EndDate	Quoter	Aggressor	Verb
TRAS_EUR	ONL	03.10.2005	09:39:04	2.08	400	03.10.2005	04.10.2005	DE0021	FR0005	Buy
TRAS_EUR	ON	03.10.2005	09:39:18	2.08	10	03.10.2005	04.10.2005	IT0162	IT0211	Sell
TRAS_EUR	ON	03.10.2005	09:45:42	2.085	50	03.10.2005	04.10.2005	IT0177	GB0005	Buy
TRAS_EUR	ON	03.10.2005	09:47:21	2.085	45	03.10.2005	04.10.2005	IT0257	IT0183	Sell
TRAS_EUR	ONL	03.10.2005	09:56:28	2.085	130	03.10.2005	04.10.2005	IT0257	IT0171	Sell

Table 1: Example of the used data set of the e-MID (Italian interbank market). Market shows the currency of the transaction. Duration shows the maturity of contract, which was traded (there are different maturities from overnight to one year). Date and Time are the date and the time when the transaction takes place. Rate is the interest rate of the contract in percent. The StartDate and the EndDate show the starting date of the contract. Quoter and Aggressor show the identity of the quoter and the aggressor bank. The quoter has placed the order in the order book and the aggressor has actively chosen the living order. Verb shows the kind of transaction from the aggressor side. So the label Sell means that the aggressor lends money to the quoter and the label Buy means that the aggressor borrows money from the quoter.

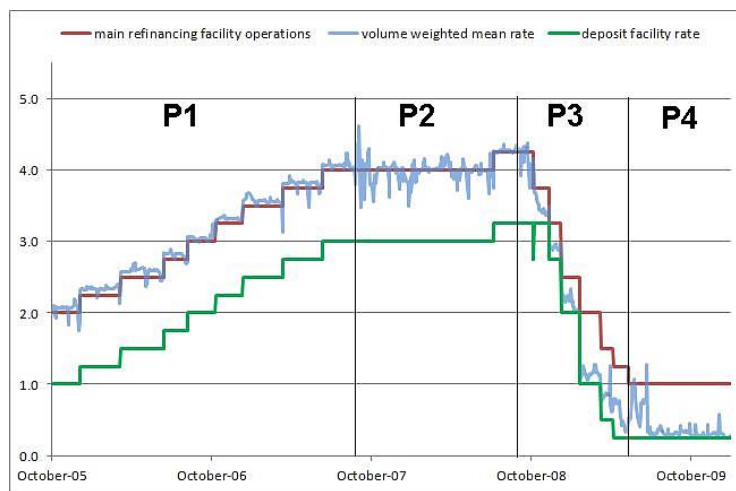


Figure 1: The volume weighted mean rate of the e-MID, the main refinancing facility operations (rate) and the deposit facility rate on daily base with the four sub periods. The e-MID rate and the main refinancing facility operations (rate) correspond before and during the crisis (till Lehman brothers collapse in September 2009), then the e-MID rate starts to correspond to the Deposit facility rate. Based on this behaviour, we decide to split the post Lehman period in two sub periods for our analysing purpose.

	P1			P2			P3			P4		
	Sq. ret.	Avg. vol.	Trades	Sq. ret.	Avg. vol.	Trades	Sq. ret.	Avg. vol.	Trades	Sq. ret.	Avg. vol.	Trades
Obs	45881	45881	45881	27257	27257	27257	16102	16102	16102	22213	22213	22213
Mean	0.0086	19.94	3.11	0.0092	17.36	2.98	0.5716	19.69	2.20	0.8513	13.68	1.71
S.D.	0.2041	19.82	2.99	0.0769	18.23	2.85	3.3016	45.16	2.46	3.5775	37.44	1.99
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	16.44	100.00	27.00	5.27	100.00	27.00	138.92	1000.00	28.00	134.67	2000.00	21.00
q05	0.0000	0.00	0.00	0.0000	0.00	0.00	0.0000	0.00	0.00	0.0000	0.00	0.00
q10	0.0000	0.00	0.00	0.0000	0.00	0.00	0.0000	0.00	0.00	0.0000	0.00	0.00
q50	0.0001	15.00	2.00	0.0004	12.78	2.00	0.0194	9.67	2.00	0.0377	7.50	1.00
q90	0.0023	45.00	7.00	0.0111	39.17	7.00	0.9931	41.71	5.00	1.8166	30.00	4.00
q95	0.0058	56.50	9.00	0.0279	52.00	8.00	2.2962	71.87	7.00	3.7374	45.07	6.00
Kurtosis	3323.14	3.85	3.98	1560.33	5.82	4.61	665.46	110.25	6.43	421.06	955.55	4.93
LB(20)	5287.78	491	2344.84	8802.05	284.01	1145.71	4422.61	277.25	1145.71	4274.57	1121.75	2290.71
MLB(20)	17876.31			21076.7			12209.94			13377.09		

Table 2: Descriptive statistics of squared log returns (multiplied by 100), average volumes per trade as well as the number of transactions based on five minutes intervals for each period. The following descriptive statistics are shown: Number of observations, mean, standard deviation, minimum, maximum, 5%-, 10%-, 50%-, 90%-, as well as 95%-quantile, kurtosis, univariate and multivariate Ljung-Box statistic (computed for squared log returns, volumes and number of trades) associated with 20 lags.

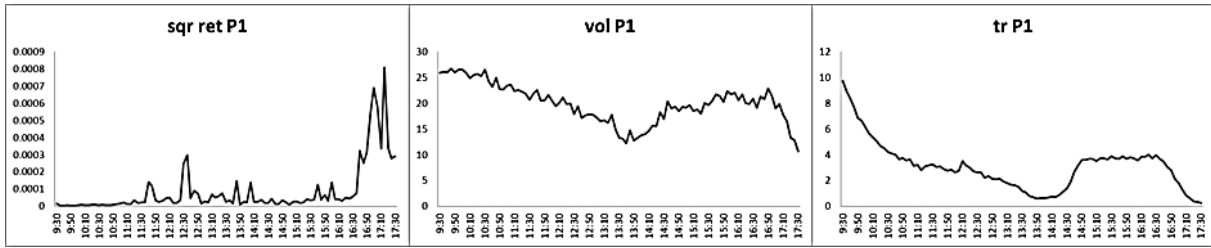


Figure 2: Intraday seasonality pattern for squared log returns (left), mean trading volume (middle) and number of trades (right) for the first period.

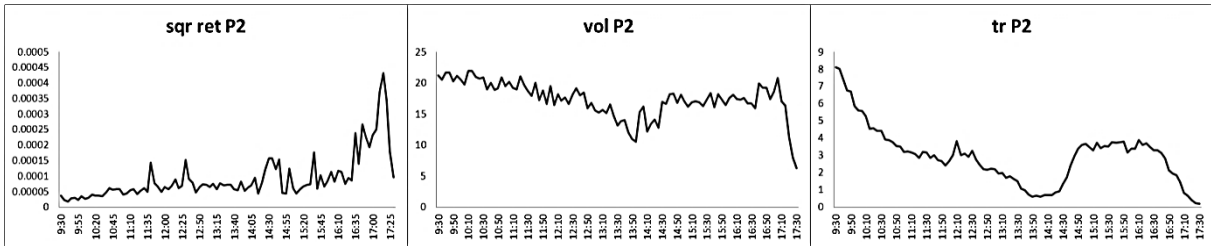


Figure 3: Intraday seasonality pattern for squared log returns (left), mean trading volume (middle) and number of trades (right) for the second period.

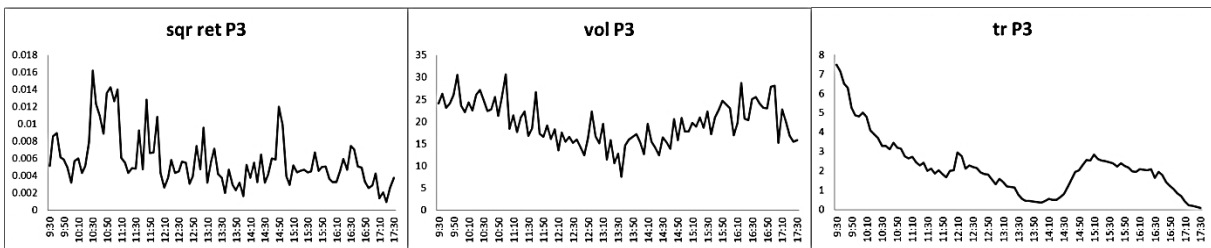


Figure 4: Intraday seasonality pattern for squared log returns (left), mean trading volume (middle) and number of trades (right) for the third period.

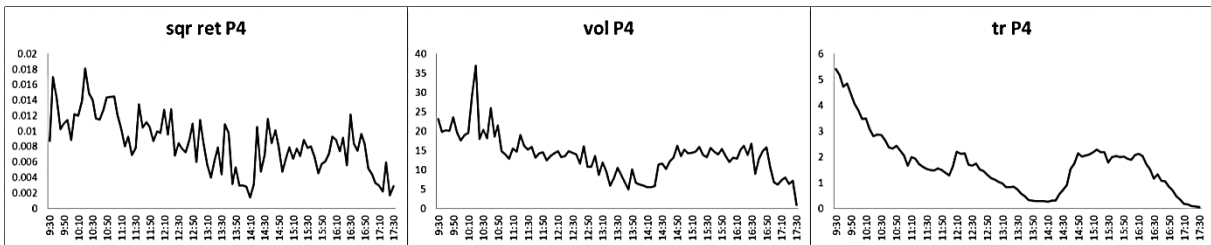


Figure 5: Intraday seasonality pattern for squared log returns (left), mean trading volume (middle) and number of trades (right) for the fourth period.

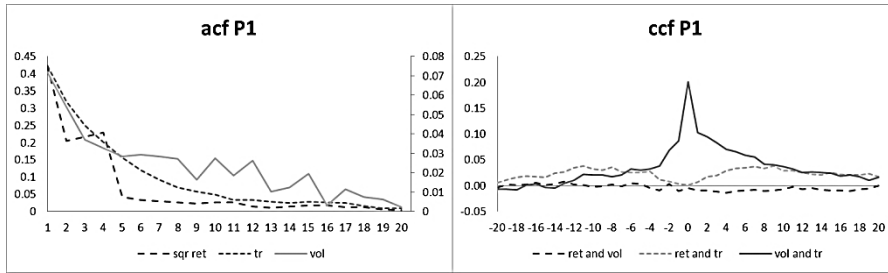


Figure 6: Autocorrelation function [acf] (left) and cross correlation function [ccf] (right) for the variables of the three dimensional framework for the first period.

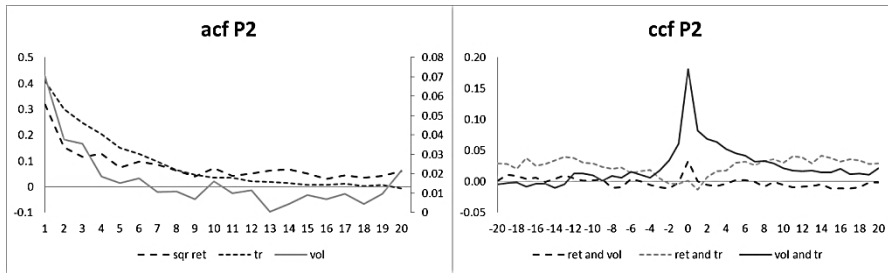


Figure 7: Autocorrelation function [acf] (left) and cross correlation function [ccf] (right) for the variables of the three dimensional framework for the second period.

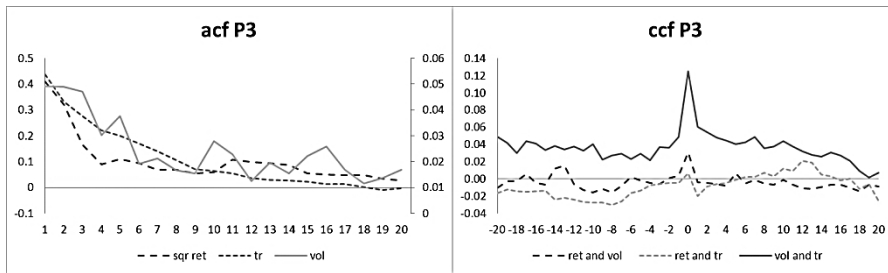


Figure 8: Autocorrelation function [acf] (left) and cross correlation function [ccf] (right) for the variables of the three dimensional framework for the third period.

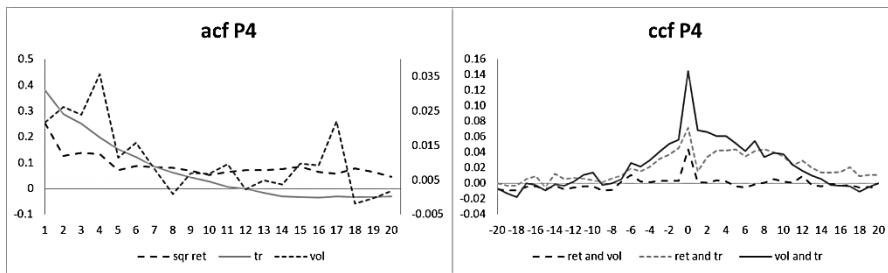


Figure 9: Autocorrelation function [acf] (left) and cross correlation function [ccf] (right) for the variables of the three dimensional framework for the fourth period.

	P1		P2		P3		P4	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
OM1	-0.7742	0.0105	-0.8279	0.0130	-0.4203	0.0127	-0.4553	0.0159
OM2	-0.1525	0.0186	-0.0690	0.0179	-0.0870	0.0115	-0.0496	0.0106
OM3	-0.2249	0.0132	-0.2697	0.0108	-0.2738	0.0169	-0.2779	0.0195
A0_12	-0.0398	0.0037	0.0449	0.0043	0.0114	0.0038	0.0434	0.0065
A0_13	-0.1527	0.0051	-0.1956	0.0068	-0.0859	0.0059	0.0597	0.0085
A0_23	0.0372	0.0105	0.0875	0.0093	0.2050	0.0070	0.2504	0.0054
A1_11	0.5489	0.0048	0.5315	0.0064	0.3716	0.0077	0.6064	0.0113
A1_12	0.0123	0.0043	-0.0187	0.0049	-0.0081	0.0029	-0.0130	0.0020
A1_13	0.2648	0.0086	0.3967	0.0094	0.1351	0.0089	-0.0051	0.0102
A1_21	0.0290	0.0100	0.0203	0.0088	0.0427	0.0057	0.0370	0.0058
A1_22	0.0871	0.0083	0.0658	0.0068	0.0570	0.0027	0.0322	0.0028
A1_23	0.0498	0.0120	0.0057	0.0112	0.0269	0.0082	0.0284	0.0072
A1_31	0.1051	0.0075	0.1154	0.0069	0.0929	0.0129	0.0689	0.0157
A1_32	0.0252	0.0054	0.0526	0.0042	0.0224	0.0035	0.0071	0.0055
A1_33	0.1252	0.0079	0.1318	0.0060	0.1791	0.0125	0.2071	0.0129
B1_11	0.9682	0.0008	0.9684	0.0009	0.9856	0.0008	0.8552	0.0046
B1_22	0.6030	0.0470	0.5540	0.0479	0.5833	0.0148	0.4722	0.0178
B1_33	0.7930	0.0161	0.7996	0.0114	0.7766	0.0222	0.6026	0.0331
LL	-48603.24		-57789.30		-32406.08		-41717.36	
BIC	-48692.37		-57878.43		-32489.91		-41802.81	

Table 3: Quasi-maximum likelihood estimation results of the MMEM for seasonally adjusted squared log returns, average trade sizes and number of trades per five-minute interval. Standard errors are computed based on the OPG covariance matrix. (Log likelihood function (LL), Bayes Information Criterion (BIC)).

Descriptive statistics of raw data												
	P1			P2			P3			P4		
	Sq. ret.	Avg. vol.	Trades	Sq. ret.	Avg. vol.	Trades	Sq. ret.	Avg. vol.	Trades	Sq. ret.	Avg. vol.	Trades
Mean	1.13	1.00	1.02	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00
S.D.	19.24	0.89	0.77	6.08	0.95	0.74	4.75	2.17	0.93	4.05	2.32	1.02
LB(20)	5287.78	491.00	2344.84	8802.05	284.01	1767.76	4422.61	277.25	1145.71	4274.57	121.75	2290.71
LB2(20)	4122.97	486.70	1944.57	963.93	125.19	831.00	624.25	42.11	41.20	2373.77	21.64	1580.96
MLB(20)	17876.31			21076.71			12209.94			13377.09		
Summary Statistics MEM Residuals												
	P1			P2			P3			P4		
	Sq. ret.	Avg. vol.	Trades	Sq. ret.	Avg. vol.	Trades	Sq. ret.	Avg. vol.	Trades	Sq. ret.	Avg. vol.	Trades
Mean	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
S.D.	7.34	0.85	0.67	3.84	0.92	0.68	2.38	1.78	0.75	2.46	2.11	0.81
LB(20)	6.15	19.53	59.10	24.21	25.42	45.00	241.95	17.94	23.67	123.43	29.39	24.78
LB2(20)	0.01	21.99	35.57	0.01	15.38	23.35	7.73	5.61	10.39	4.16	0.59	19.17
MLB(20)	196.87			602.18			383.97			84.00		

Table 4: Summary statistics of the standardized seasonality adjusted time series and the corresponding MEM residuals for the four periods. Ljung-Box statistics of the residuals (LB), squared filtered residuals (LB2) as well as multivariate Ljung-Box statistic (MLB). The Ljung-Box statistics are computed based on 20 lags.