Quantitative analysis of the Interbank credit market e-MID in the high frequency domain

Dissertation zur Erlangung des akademischen Grades
„Doktor der Wirtschafts- und Sozialwissenschaften“ (Dr. rer. pol.)

Vorgelegt im Fachbereich Wirtschaftswissenschaften
der Universität Kassel

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Tag der mündlichen Prüfung: 06.05.2020

Αφιερωμένο στην αγαπημένη μου οικογένεια…

Dedicated to my beloved family…

Zusammenfassung

Interbankenkreditmärkte, und vor allem das ungesicherte übernacht-Segment, gelten aus verschiedenen Blickwinkeln als wichtig für das gesamte Finanzsystem. So können Banken an diesen Märkten effizient Liquidität handeln oder dadurch Verpflichtungen in Zahlungs- und Abrechnungssystemen einhalten. Distorsionen in der Liquiditätsbeschaffung haben dabei negative Auswirkungen auch auf der mikroökonomischen Ebene, da diese die Kreditkonditionen von Haushalten und Firmen beeinflussen. Da Interbankenkreditmärkte als der erste Transmissionskanal der Wirtschaftspolitik gelten, spielen diese Märkte auch aus makroökonomischer Sicht eine wichtige Rolle. Dabei war das Interesse an diesen Märkten, aus praktischer und wissenschaftlicher Sicht, bis zum Ausbruch der Finanzkrise im Jahr 2007 eher limitiert. Die wesentlichsten Gründe waren dabei die gute Funktionsweise der Märkte und die geringe Fristigkeit der Kredite. Dies änderte sich mit dem Ausbruch der Finanzkrise im August 2007. Ein wesentliches Problem der Analyse der Interbankenkreditmärkte ist dabei die Datenverfügbarkeit. Im Rahmen der vorliegenden Dissertation wird ein Datensatz des einzigen organisierten Interbankkreditmarktes in der Eurozone und den USA, dem e-MID Markt, als Datengrundlage verwendet. Der Fokus liegt hier auf den Übernachtkrediten da diese den Großteil der Transaktionen widerspiegeln. Ein weiterer Fokus wird auf die verschiedenen Marktzustände vor, während und nach der Finanzkrise von 2007 ff. gelegt.

Die ersten beiden Kapitel der Dissertation widmen sich den Intratageszinskurven und somit der Frage wie sich Interbankenzinsen im Tagesablauf verändern. Im ersten Kapitel wird dabei zum ersten Mal gezeigt, dass die Zinsen mit Hilfe des nichtlinearen Nelson Siegel Models empirisch modelliert werden können. Die Ergebnisse suggerieren, dass die Zinsen nicht nur lineare und vor allem fallende Verläufe haben, wie es bisher angenommen wurde, sondern auch nicht-Linearitäten eine tragende Rolle spielen können. Weiterhin wird eine hohe Anpassungsgüte erreicht, welche insbesondere in Zeiten der Krise signifikant hoch ist.

Im Rahmen des zweiten Kapitels werden erstmalig drei Modelle zur Schätzung dieser Intratageszinskurven mit einander verglichen. Die empirischen Ergebnisse zeigen, dass alle drei Modelle für die Schätzung der Intratageszinskurven geeignet sind und, dass dabei das Svensson Modell gegenüber den anderen beiden Modellen bevorzugt werden sollte.

Das dritte Kapitel umfasst die Analyse der Transaktionen und Volumina im Tagesablauf. Hier werden erstmalig die Transaktionen unterteilt in Kaufs- und Verkaufstransaktionen, und deren Verläufe unter Einbezug verschiedener Marktzustände miteinander verglichen. Die empirischen Ergebnisse suggerieren, dass diese Verläufe sowohl aus ökonomischer als auch ökonometrischer Sicht nicht vernachlässigt werden sollten.

Abstract

Interbank credit markets, and especially the unsecured overnight segment, are important for the entire financial system from various perspectives. On these markets banks can efficiently trade liquidity or thereby comply with obligations in payment and settlement systems. Distortions in the procurement of liquidity also have a negative impact on the microeconomic level, as these affect the credit conditions of households and firms. Since interbank credit markets are considered as the first transmission channel of economic policy, these markets also play an important role from a macroeconomic perspective. From a practical and scientific perspective, interest in these markets was rather limited until the outbreak of the financial crisis in 2007. The main reasons were the good functioning of the markets and the short term of the loans. This changed with the outbreak of the financial crisis in August 2007.

A major problem in the analysis of the interbank credit markets is the availability of data. In the context of this dissertation, a data set of the only organized interbank credit market in the Eurozone and the USA, the e-MID market, is used as a data basis. The focus here is on overnight loans as these reflect the majority of the transactions. Another focus will be on the different market conditions before, during and after the financial crisis of 2007 and onwards.

The first two chapters of the dissertation are devoted to intraday yield curves and thus to the question of how interbank rates change during the day. The first chapter shows for the first time that interest rates can be modeled empirically using the non-linear Nelson Siegel model. The results suggest that interest rates are not only linear and, above all, falling, as previously assumed, but that non-linearities can also play a major role. Furthermore, a high level of adaptation is achieved, which is significantly high, particularly in times of crisis.

In the second chapter, three models for estimating these intraday yield curves are compared for the first time. The empirical results show that all three models are suitable for estimating the intraday yield curves and that the Svensson model should be preferred over the other two models.

The third chapter includes the analysis of daily transactions and volumes on the e-MID market. Here, for the first time, the transactions are divided into buy and sell transactions, and their distributions are compared with one another, taking into account different market conditions. The empirical results suggest that these trends should not be neglected from both an economic and an econometric point of view.

II. List of abbreviations

BBA	British Bankers Association
BIS	Bank for International Settlements
BUBOR	Budapest Interbank Offer Rate
DLM	Diebold- Li Model
ECB	European Central Bank
ECB	European Central Bank
EFTA	European Free Trade Association
e-MID	Mercato Interbancario dei Depositi
EONIA	European Overnight Index Average
EURIBOR	European Interbank Offered Rate
HIBOR	Hong Kong Interbank Offered Rate
LIBOR	London Interbank Offered Rate
MAE	Mean Absolute Error
MIBOR	Mumbai Interbank Offered Rate
NSM	Nelson- Siegel Model
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
ON	Overnight
ONL	Overnight Large
RMSE	Root Mean Squared Error
SHIBOR	Shanghai Interbank Offered Rate
SIYC	Spot Intraday Yield Curve
SVM	Svensson Model

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Acknowledgments

The project of my dissertation could not have been successful without the active and true support of many people.

First and foremost, I would like to thank my doctoral supervisor Christian Klein from the Department of Corporate Finance. Prof. Klein, thank you very much for agreeing to accept me as a doctoral student. Without you, this project could not have taken place. I would like to thank you for your flexibility and your positive input at every stage of my dissertation.

Furthermore, I would like to thank my supervisor in charge and second reviewer Vahidin Jeleskovic. Thank you very much Vahidin for the endless hours of our discussions and your invaluable assistance in the context of my dissertation. Your care has not only educated me scientifically, but also personally. I have been able to learn a lot from you in the last few years and will certainly not forget this time. Hvala vam za sve Vahidine.

I would also like to thank Jochen Michaelis warmly for his time to review my dissertation. Although I was not employed by you, you were there from the beginning of my dissertation with words and deeds. I would like to thank you for listening to me at any time and answering many questions about conferences, publishing and other scientific issues. Furthermore, without your efforts and assistance in providing funding, it would not have been possible to attend numerous conferences. In this context I would also like to thank Heike Krönung for her secretarial support regarding conferences and other aspects. Than you Heike for your kind assistance.

During the first years of my doctorate, I worked for numerous chairs of the Department of Economics, thus allowing me to effectively work on my PhD. I would like to sincerely thank Frank Beckenbach, Rainer Voßkamp, Georg von Wangenheim and Heike Wetzel for having hired me as a research assistant in recent years. Thank you also Sandra Ohly, who made it possible for me to be a part of the REPRTE project. Thank you Astrid Dannenberg for hiring me as coordinator of the Master in Sustainable Economics.

Another thank you goes to Björn Frank. Thank you very much Björn, for your cooperation in recent years in the framework of the REPRTE project and the appointment as a research assistant. I would like to thank you also for the many tips you have given me in recent years.

Furthermore, I would like to thank the Berufsakademie Rhein- Main and especially Mr. Bernd Albrecht for their cooperation. I am proud to have represented the Department of Economics in recent years.

I want to thank all my employers for their trust in the last years.

I would also like to thank for their helpful comments the participants at the conferences in Paris, France (Business and Social Science Research Conference, 2014), Poznan, Poland (1st ICOFEP, International Conference on Finance and Economic Policy), Rethymno, Greece (22nd and 23rd ICMAIF, International Conference on Macroeconomic Analysis and International Finance), Glasgow, Scotland (17th INFINITI, Conference in International Finance) and in Leipzig, Germany (Conference of the German Economic Association/ Jahrestagung des Vereins für Socialpolitik, 2019).

Furthermore, thanks to my friends in and around the university who always stood by me. You all know who I mean. A big thank you to you all!

Where would I be without my family? A big thank you goes to my parents, Litza and Jiorgo. You have given me the wings to fly as far as possible as I wish. You made it possible for me to take my first academic steps by coming to Germany in 2008. Mom and Dad, thank you for your love and faith in me! Special thanks also goes to my brother Niko. Thank you, for always believing in me! I would also like to thank my "new family". Many thanks to my in-laws Olga and Vladimir, my brothers-in-law Edward and Alexander. I love you all and I am happy that I was able to make you a bit proud of this work.

Last, but of course not least, my deepest gratitude goes to my children Olia and Jiorgo and my wife Veronika. Olia and Jiorgo, you are the meaning of my life, no matter how difficult the days appeared, with you I always saw the sun on the horizon. Your smile is what drives me on. What should I write about my wife Veronika now? The love of my life ... Without you, I would never have been able to complete this dissertation successfully. You were always there for me, no matter how frustrated, tired or angry I was. You've taken over so many things from me so I can have some more time for writing. You put your own desires and dreams aside, so I can achieve my goals! I would like to thank you for all this and much more! A thank you is certainly not enough and I hope that I will have many years to come with you to show you how grateful I am to be with you…

Introduction

The present monograph represents my cumulative dissertation, which was written at the University of Kassel, Faculty of Economics and Business Administration in the years from 2015 to 2019. The primary topic is the quantitative analysis of the interbank credit market e-MID (*Mercato dei Depositi Interbancario*) in the high-frequency domain.

Here, high frequency means that the analysis focuses on the dynamics of the intraday interest rates based on the intraday yield curve. For this purpose, a new concept of the intraday yield curves is introduced, analyzing them in chapters 1 and 2 from an empirical and theoretical point of view. In the center of interest in chapter 3 are the dynamics of the number of transactions and the volume of transactions on an intraday basis. Special focus was put in each chapter also onto different market states around major events of the financial crisis of 2007 and onwards. The analyses and findings which I present in this monograph are of high interest from different points of view. Among others they include: From a banking perspective, they play a major role in the liquidity management and the optimization of their trading strategies on an intraday basis. From a monetary policy view, a well-functioning interbank credit market is of high interest. Distortions on these markets led to the outbreak of the financial crisis in 2007 so, also from a macroeconomic point of view this analysis is of great interest. Additionally, these distortions affect also the lending conditions of households and firms. Hence, also from a microeconomic point of view, the findings presented in this monograph can be considered as interesting.

Besides the introduction, each of the following chapters in this monograph presents a scientific article. The first article in chapter 1 and the second article in chapter 2 were written together with my supervisor in charge and second reviewer Vahidin Jeleskovic. The third article which represents chapter 3 was written in single authorship. All three chapters have been published as discussion papers in the Discussion Paper series MAGKS.

The article in chapter 2 has been published in Journal of Corporate Accounting and Finance. In addition to the publication as a discussion paper, the other two articles have already been submitted to peer-reviewed journals with the goal of an internationally recognized publication in the near future. The adoption of the concept of a cumulative dissertation results in a few recurrences, especially when it comes to the presentation of the data sample (even though there are slight differences in the used data sample in each chapter) or the presentation of the e-MID market in each of the following chapters of the monograph.

Until the outbreak of the financial crisis of 2007, research and practical interest which was put in the analysis of interbank credit markets can be considered as low (Hatzopoulos and Iori, 2012). This was the fact because these markets where functioning well, meaning that the distribution of liquidity was given at any time point. This changed after the outbreak of the global financial crisis in August in 2007 and even more with the worsening of the crisis after the collapse of the investment bank Lehman Brothers in September 2008. De Socio (2013) compares the interbank credit market with a plumbing system, a system whose importance is only taken into account when it breaks down. This comparison of De Socio (2013) becomes even clearer when we consider that distortions on the worldwide interbank credit markets indicated the outbreak of the financial crisis of 2007 and onwards (Green, 2011).

On the interbank credit markets, the majority of the transactions are overnight transactions, meaning that the credit partners agree that the credit must be repaid on the following business day. This intraday liquidity is essential in order to overcome short liquidity demands or to settle obligations in payment and settlement systems (Ball et al., 2011). This kind of lending activity may also be called “next to last resort” (Green et al., 2016). Distortions of the liquidity supply in turn also have a negative impact on the real economy, since they affect the conditions of borrowing of households and firms (Angelini et al., 2011).

Furthermore, interbank credit markets and especially the unsecured overnight segment, are the first monetary policy transmission mechanism in the financial system and are often used by policymakers as a catalyst for monetary policy decisions. In order to achieve an efficient monetary policy, the functions of interbank credit markets and the determinants of interbank rates must not be ignored by the policy makers. In times of economic stability, interbank rates are almost entirely determined by prevailing monetary policy orientations. This explains the phenomenon of central banks being disturbed by the developments in the interbank credit market after the outbreak of the financial crisis (Angelini et al., 2011).

Many overnight interbank credit rates (which are also called interbank credit markets) do exist. For the Eurozone, the most well-known are the following:

The EONIA (Euro OverNight Index Average), which was established in 1999 and is the interest rate for unsecured overnight credit transactions in the interbank credit market of the European Union and the European Free Trade Association (EFTA). The EONIA is calculated on a daily basis with the help of the European Central Bank. It is often referred to as the overnight EURIBOR (Euro InterBank Offered Rate). The EURIBOR is an interbank interest rate at which large banks in the European Union can grant each other unsecured loans for a prescribed period of time. This rate is published daily. The EURIBOR includes both weekly credit transactions of one, two and three weeks as well as monthly credit transactions of one to twelve months.

The London Interbank Offered Rate (LIBOR) has been another reference rate on global interbank credit markets since 1986. There are a variety of LIBOR rates, including interest rates with seven different maturities (overnight, one week, one month, two months, three months, six months and twelve months) and five different currencies (the US dollar, the British pound, the euro, the Japanese yen and the Swiss franc). The official LIBOR rates are announced once a day on behalf of the British Bankers Association (BBA).

In the US the most well-known rate for overnight interbank credits is the overnight federal funds rate. Important overnight interbank rates in Asia are the overnight SHIBOR (Shanghai interbank offered rate) the overnight MIBOR (Mumbai interbank offered rate) and the overnight HIBOR (Hong Kong interbank offered rate).[1] All these afore mentioned interbank rates are used in the financial markets as the base rate for a large number of financial products such as futures, swaps or options.

Even though our understanding of the international interbank credit markets improved in the last few years, especially after the outbreak of the financial crisis, we still do not know much about how these markets function in detail (Allen et al., 2019). One of the reasons why we cannot take a closer look at these markets is the missing data, as e.g. Spelta et al. (2019) state for the EONIA market.

The data availability problem vanishes for the Italian interbank credit market e-MID. This market is the only organized electronic market for interbank credits / interbank deposits in the entire euro zone and the US (Gabbi et al., 2012). The e-MID market was founded in 1990 as an initiative of the Bank of Italy, and the trading volume and number of transactions increased systematically in the market until the outbreak of the global financial crisis in August 2007. The data sets are commercially available via the company e-MID Sim S.p.A. which manages the market. This market can be characterized as a benchmark for the Euro area money market (Beaupain and Durré, 2011, Arciero et al., 2016), especially on the overnight maturity. Furthermore, this market was taken into account in many analyses of different policy makers, e.g. the European Central Bank (Beaupain and Durré, 2013) and stated for about 17% of the total turnover of the unsecured money market in the Eurozone before the outbreak of the crisis (ECB, 2011).

[1] For a detailed look of the interbank credit market in the overnight segment see Green et al. (2016)

The basis of the analysis in this monograph is an e-MID data sample which spans from 03.10.2005 until 31.03.2010, by taking into account the overnight segment of the market. This large data sample was chosen due to the fact that it includes a pre-crisis period, the crisis period and an after crisis period around the events of the outbreak of the financial crisis in August 2007. Due to the fact that the different market states, with respect to major events of the financial crisis, are being explicitly taken into account in this monograph, the data sample is divided into four sub-samples. The construction of the different sub-samples is based also on the arguments proposed in different analyses by e.g. Gabbi et al. (2012). The first period spans from 03.10.2005 to the 07.08.2007, one day before the outbreak of the financial crisis. This period is regarded as the pre-crisis period. The second period ranges from 09.08.2007, the day of outbreak of the financial crisis until 14.09.2008, one day before the collapse of the bank Lehman Brothers. This period is called the first crisis period. The third period spans from 15.09.2008, the day of the Lehman Bank collapse until the 12.05.2009, one day before the last reduction of the key interest rate by the ECB in the data sample. This period is called the second crisis period. The last period ranges from 13.05.2009, which is the key interest reduction day, until the sample end on the 31.03.2010. This period is called the after crisis period. During the first two periods the liquidity provision between banks is still working, meaning that the market mechanism is still intact. During the last two periods the market is no longer working properly, and the liquidity provision of the banks has been taken up mainly by the ECB.

During the period of the data sample a total number of 426,392 credit transactions were completed on the e-MID market. The total volume of these credit transactions equals 18,363,228.12 million Euro. Out of these, around 90%, in terms of number and volume of transactions, are overnight (ON) transactions. During that sample period, 210 banks from 16 different countries were active on the market, either as a credit lender or as a credit borrower. These countries include: Austria, Belgium, Denmark, Germany, Finland, France, Great Britain, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland and Portugal and Switzerland.

The use of a data sample after 2010 does not seem to be necessary since the market becomes even more illiquid after 2010, meaning that the mean volume traded per day becomes even lower. After 2010, the main provision of liquidity is given by the ECB and the interbank credit markets become less relevant (Barucca and Lillo, 2018).

Let us now take a closer look at the three different chapters of this monograph.

In chapter 1 of the monograph we introduce a major novelty, which is the empirical estimation of nonlinear spot intraday yield curves (SIYC) on the e-MID market using the Nelson- Siegel model (Nelson and Siegel, 1987) based on tick-by-tick data.

The shape of the yield curve has been interpreted in different studies mainly from a macroeconomic point of view. A monotone increasing yield curve may indicate an accelerating economy, resulting in higher expected interest rates in the future, whereas a monotone decreasing yield curve may indicate a coming downturn in the economy. A hump-shaped yield curve (with a positive or negative sign) may be caused by similar expectations for the short and long run but different expectations for the medium term. Attempts to explain this phenomenon may be through the market segmentation theory (Culbertson, 1957, Modigliani and Sutch, 1966). Moreover, a flat yield curve may either indicate similar expectations for future developments or very high uncertainty in the market about future developments (Estrella and Hardouvelis, 1991, Estrella and Mishkin, 1999). Thus, the form of each yield curve on different credit markets may have a huge impact on market participants and their investment decisions. To maximize their own profits, market participants consider the difference between short- and long-term interest rates. Furthermore, Aljinović et al. (2012) state that a variety of activities in the financial markets is determined by the relationship between the maturity and interest rates; this relationship may play a crucial role in microeconomic, macroeconomic, and financial questions. Additionally, in the Nelson- Siegel model for the interest rates on three months and longer maturities, spot rates start at current short-term rates, determined by monetary policy (the starting point), and are governed at intermediate horizons by expectations of the business cycle, inflation, and monetary policy (the hump). They may eventually become steady in the long-run if such expectations predominate in the market (Gürkaynak et al., 2007).

The first study contributes to the literature in different major ways: First, it contributes to the existing literature of studies focusing on the estimation of an intraday term structure on the e-MID, namely the studies (primary) of Angelini (2000), Baglioni and Monticini (2008), Baglioni and Monticini (2010) and Baglioni and Monticini (2013), who all use linear models in their estimations, whereas, in contrast we use a nonlinear model. As stated during this analysis, we use tick-by-tick data, whereas the other previously mentioned studies use data samples with respect to a higher intraday frequency, namely, hourly means of the interest rate.
All these studies show, a, more or less, term structure with a downward trend which becomes more important after the outbreak of the financial crisis in 2007. In contrast, we show that there is not only a linear relationship between interest rates and the maturity of the overnight credits. Furthermore, it contributes to the literature of yield curve estimation, since we use the Nelson-Siegel model, which represents a model which has been empirically verified in different studies

and is also used by different central banks for the estimation of yield curves (BIS, 2005). Additionally, in this first study we implement a new concept for the maturity of each interbank transaction on the e-MID market. This implementation differs from the maturity concepts used in the previous studies.

From a practical point of view, it is the first study which shows that the SIYC on the e-MID and in general on an interbank credit market can be modeled by standard models, the Nelson-Siegel model, for the estimation of yield curves, based on our concept of the SIYC. We also show that one must move away from the assumption of the linear models and that these non-linear dynamics in the intraday yield curve where highly noticeable during the turmoil which results in a significant better goodness of fit. Therefore, we state that the banks which are actively participating in the e-MID market base their credit involvement decisions on the intraday dynamics of intraday interest rates especially during a financial crisis. Additionally, based on our introduced concept of the SIYC, the Nelson- Siegel model is capable of identifying the different periods and market states. This fact is shown by the statistically different values of the R^2 in each period. As mentioned, during this study we base our analysis on the original tick-by-tick data. In the previously mentioned studies, the authors use one-hour intervals, meaning one-hour means of the interest rate for their estimations. Although our data sample becomes more volatile, our results based on the goodness of fit indicate superiority.

Based on our findings, there are further research questions that are interesting to be answered in the near future from a theoretical and a practical point of view. First, one could estimate the SIYC by differentiating between a curve for credit lenders and credit borrowers and analyze if there are significant differences between these curves. What is also of high interest may be to take a closer look on the SIYC before and after more major events, e.g. the collapse of different banks or changes in the federal funds rates. Furthermore, Hartmann et al. (2001) find out, that slightly before or on the 23rd business day on each month, when the reserve maintenance period ends, the overnight rates may show a short peak or fall. They state that this fact can be explained in such a way, that banks test the market early in the morning with quotes which are not acceptable for the liquidity management. Palombini (2003) also points out such changes in the volatility of interest rates before the end of the maintenance period. Even though we highlighted the fact that the maintenance period has some impact on the SIYC, due to saisonalities around the 23rd business day of each month, the effect of the reserve maintenance period could be taken into account in a more detailed way in order to test the exact influence of this fact. These kinds of analyses could be done using an event study.

At the end of this first study we state that it would be of interest to compare different standard models for the estimation of the SIYC. This is the major focus of the second chapter of this monograph.

In the second chapter we compare three different (standard) models for the estimation of the SIYC on the e-MID market, namely the Nelson-Siegel model (Nelson and Siegel, 1987), the Svensson model (Svensson, 1994) and the Diebold-Li model (Diebold and Li, 2006). These models are being used mainly on lower frequencies for the estimation of government bond yield curves. For this purpose, we use different in-sample statistics, namely the R^2, the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE). During this analysis we move away from the tick-by-tick data use and take into account 30-minute intervals for our estimation. This is done since we believe it is a good mix of empirical results and the practical point of view, whereas other studies in this field (Angelini, 2000, Baglioni and Monticini, 2008 Baglioni and Monticini, 2010 and Baglioni and Monticini, 2013) use intervals with a lower frequency, namely one-hour intervals.

Moreover, here the contribution to the existing research questions and the literature is manifold: First, in this study we show that besides the Nelson- Model, also the Svensson model and the Diebold-Li model are highly suitable to estimate the SIYC on an interbank credit market, and more especially on the e-MID market. Here we provide superior empirical results when our findings are compared with similar works on this market. This fact is shown in the different in-sample goodness of- it statistics, namely the R^2, the MAE and the RMSE. Furthermore, the models are capable of the estimation of the SIYC also during the different market states. Additionally, this study represents the first comparison study of different methods for such an intraday term structure estimation.

We do find out, that all models are suitable for the estimation, but we also prove empirically that the Svensson model dominates the other two models on all considered sub-periods and different market states based on all in sample statistics. Additionally, we show in this analysis that the Svensson model is capable of detecting the different market states in the four previously mentioned periods using the three in-sample statistics. We therefore state here that the Svensson model is to be used when it comes to the modelling of the SIYC and the identification of different market states on the e-MID market. Furthermore, we can state that the comparison of the Nelson-Siegel model and the Diebold-Li model shows that the Nelson- Siegel model may dominate the Diebold-Li model in the different periods, although these differences are not statistically significant. The Nelson-Siegel model is to be preferred only when the market functions properly, meaning in periods one and two.

Until this time period chapters 1 and 2 of this monograph represent the only studies focusing on the estimation of nonlinear yield curves, in general, on the interbank credit market in the intraday domain, and on the e-MID in particular. By taking into account the findings which will be presented in the above-mentioned chapters and the better results in the goodness of fit of the estimation, it is of great interest to take into account also the forecasting of the interest rate based on these nonlinear constructs in the future.

After taking into account the changes of the interest rate during the day in different markets states the main research focus of the third chapter is the analysis of the distributions of the number of transactions and the volume of transactions (absolute and mean per transactions) in the intraday frequency on the interbank credit market e-MID. Special focus is put also in this chapter on the different markets states. Great attention is furthermore paid here to the differentiation between the buy and sell transactions.

The contribution of this chapter is also manifold: First it is to analyze the distribution of number of trades and volume (absolute and mean per transaction) by separating the buy and sell transactions and to show the changes among the different markets states in the previously described data sample. Although different studies focus on the intraday distribution of these measurements e.g. Angelini (2000) and Beaupain and Durré (2008) (see section 3.2 for further details), this study represents the first analysis of these variables by differentiating buy and sell transactions in different markets states.

The number of transactions and the volume of transactions in the intraday frequency are important for different reasons. These include a better understanding of the functioning mechanisms of the interbank credit markets in general and the optimization of the banks trading strategies during the day. Furthermore, a special focus is put on the detection of recurring distributions of these variables due to the fact that these can be seen as the basis of further empirical or econometrical analyses e.g. for the implementation agent-based models. Additionally, also from a monetary policy point of view, the findings presented in this chapter are of high interest for the real economy also.

The analysis in chapter 3 reveals some interesting facts. By taking into account the number of transactions and the absolute volume of transactions and their distributions, we can see that in all different market states the distribution follows a double U-shape. This double U-shape means that small values of these variables can be detected as the market opens, takes higher values in the time intervals at around 10:00 and small values until noon. Afterwards another upward trend can be detected until approximately one hour before the market closes. From this time point again the values of the variables show a downward trend until the closing of the market at 18:00. Another important implication which can be found here is, that when the market is not functioning properly anymore, which is the fact after the collapse of the bank Lehman Brothers, banks shift their activities to earlier during the day. This fact can be seen in the distributions of the two variables, since the double U-shape is still intact, but the second hump is earlier during the day.

Moreover, this analysis detects recurring distributions in all periods and market states. Such recurrences can be called also stylized facts of the e-MID market. A stylized fact is defined as a statistical property which stays stable over the time in the different periods and robust in terms of estimates (Winker and Jeleskovic, 2007). During the whole data sample, in all market states, the number and the absolute volume of the sell transactions are higher than these of the buy transactions. Moreover, this is also the case in all analyzed intraday intervals. This stylized fact highlights again the case that banks use the e-market primarily to deposit excessive liquidity and has not been reported in a previous study on the e-MID market. Due to stylized facts like these, various econometric, economic or agent-based models were developed, in order to explain these phenomena on the different segments of the financial markets (Cont, 2001). Thus, results of this chapter can be seen as the basis for further analyses on interbank credit markets. By taking into account the distribution of the mean volume per transaction during the day, we will see that the distribution follows a three-peaked shape. High values of this variable can be found as the market opens, around noon and before the market closes. These trends can be observed in all market states. The fact that the measurements of the sell transactions here are higher than these of the buy transactions cannot be observed. On the other hand, the values of the buy transactions are mainly higher in all markets states, but in some intervals during the day the mean amount per transaction for the sell transactions are higher.

By considering this analysis, further research questions can be obtained: During the analysis I highlight the fact that also on other segments of the financial market, e.g. the stock market (Ozturk et al., 2017), the distribution of the volume and the number of trades follows a U-shape. It would be interesting to analyze whether the changes in the intraday distribution on other segments of the financial markets affect the distributions of the variables on the interbank credits market and on the e-MID market in particular. Furthermore, it would be interesting to analyze the distribution of the variables by comparing different countries of origin or to take into account credits with a lower frequency, e.g. credits with a maturity of one week or one month and their changes in the different market states.

As it can be seen, different research questions and different contributions are being made during this monograph. The data set of the e-MID market makes it possible to analyze different aspects of the interbank credit market from a theoretical and practical point of view. Based on the findings of this monograph many further research aspects are highlighted which will be in the center of attention during my next academic steps.

1. Empirical estimation of intraday yield curves on the Italian interbank credit market e-MID

1.1 Introduction

The yield curve, which models the relationship between interest rates and various maturities and thus quantifies the interest rate movements based on the maturity of bonds or credits, has been analyzed, especially from a macroeconomic point of view, in many studies (e.g. Ang and Piazzesi, 2003, Diebold et al., 2005, Piazzesi, 2005, Diebold et al., 2006, Rudebusch and Wu, 2008, Afonso and Martins, 2012). Furthermore, several researchers have analyzed the effects of the recent financial crisis on interest rates, in particular on the yield curve (e.g. Guidolin and Tam, 2014).

The model of Nelson and Siegel (1987) (hereafter NSM) presents a breakthrough in the parsimonious modeling of yield curves and is often used in both theory and practice due to its empirically proven goodness-of-fit and the implied conforming behavior of long-term yields (Niu and Zeng, 2012, Aljinović et al., 2012). The NSM has been empirically verified by different researchers (see e.g. Ganchev, 2009, Kladivko, 2010, Aljinović et al., 2012). In this line, the NSM is used by many researchers (see, e.g., Hladikova and Radova, 2012, Cassino et al., 2014, Meier, 1999), individual investors as well as large banks and central banks, including those of Belgium, Finland and Italy (BIS, 2005).[2] Furthermore, the model is used also by practitioners, for example, by fixed income portfolio managers, to strengthen their portfolios (Hodges and Parekh, 2006).

Only a few studies focus on the estimation of the yield curve on different interbank credit markets. Due to the reliability of those markets and the short maturity of the interbank credits, there was no strong research focus on interbank credit markets until the outbreak of the financial crisis in 2007 (De Socio, 2013, Hatzopoulos and Iori, 2012). Hurn et al. (1995) estimate the yield curve for the LIBOR of one, three, six and twelve months. Ametrano and Bianchetti (2009) estimate the yield curve for the EURIBOR of one, three, six and twelve months. Reppa (2008) estimates the yield curve using, among other rates, BUBOR (Budapest Interbank Offer Rate) rates for maturities of two weeks and from one to twelve months.[3]

[2] For the economic interpretation of the yield curve see e.g. Estrella and Hardouvelis, 1991, Estrella and Mishkin,1999 and for the NSM e.g. Gürkaynak et al., 2007.

[3] These research works all apply different methods.

The question arises as to why banks participate in the interbank credit markets. The primary function of those markets is to allocate liquidity among banks. This liquidity is originally provided by the central bank of each banking system (Wiemers and Neyer, 2003). However, banks may generate a liquidity crunch, expect one, or may alternatively generate a liquidity surplus. In both cases, banks might be motivated to act on interbank credit markets (Vento and La Ganga, 2009a). This may also be the case for the interbank credit markets on intraday time frequencies. Thus, the price of intraday money, that is the intraday interest rate, affects the liquidity management of those banks and moreover, is also informative in order to understand the payment system as well as the implications of different policies of central banks, by providing intraday credits (Baglioni and Monticini, 2008) and in order to settle obligations in payment and settlement systems (Ball et al., 2011).
The interbank credit markets are also crucial to the functionality of all financial systems. The interbank credit market is the first channel of monetary policy transmission and plays an important role for the borrowing and lending of households and firms (Affinito, 2012). Furthermore, a well-functioning interbank market channels liquidity effectively from institutions with a cash surplus to institutions with cash shortages. From a policy maker's point of view, a well-functioning interbank credit market is of high interest, since it helps to achieve the desired interest rates, which allows to trade liquidity effectively (Furfine, 2002).
Most interbank credit markets are over-the-counter markets. There, market prices (interest rates) and transaction volumes are not publicly known. One exception is the Italian electronic interbank credit market - Mercato dei Depositi Interbancario – e-MID (Bonner and Eijffinger, 2013).

Therefore, the goal of this paper is the estimation and empirical analysis of the spot intraday yield curves (hereafter SIYC-s) for the e-MID, a fully transparent market and the only electronic market for interbank deposits in the Eurozone and the US (Hatzopoulos et al., 2015). According to data from the European Central Bank (ECB) this market accounted for about 17% of the total turnover in the unsecured money market in the Eurozone before the financial crisis (ECB, 2011). Furthermore, one advantage of this market is that the rates on the e-MID reflect actual transactions and do not suffer from potential distortions affecting other rates, such as the LIBOR or the EURIBOR (Angelini et al., 2011).

Due to the fact that the overnight segment is the most important segment of the interbank credit market (Green et al., 2016) and given our calculations that about 90% of credits, in terms of volume and absolute number of credits, on the e-MID are overnight credits, it is intuitive to first look into the intraday dynamics of the yield curve of overnight credits and to model them by applying the NSM.

There is a certain amount of published papers and studies of econometric modeling and estimating the yield curve on low frequency using NSM (and its extensions and modifications). However, to the best of our best knowledge, there are no such papers analyzing the SIYC-s on interbank credit markets.

On the other side, there is a certain amount of papers analyzing the intraday interest rate on the e-MID. Angelini (2000) was the first to analyze the intraday rate in the e-MID from July 1993 to December 1996 by constructing an intraday curve using hourly means of the intraday interest rates. During his analysis, he finds only some weak evidence for a downward intraday interest rate.

Baglioni and Monticini (2008) also postulate a concept of an intraday interbank rate curve for the e-MID market, starting with the question whether there is a market price for intraday money on the e-MID market. In this context, the authors claim, using hourly averages of the intraday interest rate, that there is an implicit intraday interest rate whenever the overnight interest rates differ within an operating day and depending on the intraday time point at which the overnight credit contract was traded. Their empirical results are in line with the expected theoretical findings that the intraday rate curve shows a clear, but low, downward pattern throughout the operating days in 2003 and 2004.[4]

Baglioni and Monticini (2010) redo this analysis for 2007, using hourly means, to compare the intraday curve before and after the outbreak of the financial crisis. They find some clear signals for a downward trend of the intraday interest rate especially after the outbreak of the financial crisis in 2007.

Baglioni and Monticini (2013), using also hourly means for the estimation of the intraday rate curve, also find a higher downward trend of the intraday interest rate after the onset of the financial crisis in 2007 and even more after the collapse of Lehman Brothers in 2008.

[4] Moreover, this question may be also very important from the point of view of the central bank which is interested to understand the implications of its different policies in the provision of intraday credits. The objects of interest are credits with shorter maturity than one day.

Also, Gabbi et al. (2012) analyze the intraday behavior of interest rates, using a sample from 1999 to 2009. They find a stable intraday interest rate before the crisis and a significant downward trend after the outbreak of the financial crisis. According to Gabbi et al. (2012), this effect becomes larger after the collapse of Lehman Brothers.

Other researchers, e.g., Raddant (2014) analyze the intraday interest rate on the e-MID, using a complex construct for the depended variable based on interest rates. First, the results of such analyses are not clear from both the theoretical as well as the practical point of view because the dynamic of such a complex constructed variable is unknown and not directly observable on the market. Besides, such analyses may also attract little interest from the practical point of view in terms of applying trading strategies.

Moreover, other intraday interest rate constructs, including the papers by Abbassi et al. (2017), using secured funding data, Jurgilas and Žikeš (2013) and Merrouche and Schanz (2010) in the UK, and Furfine (2001 and 2002) in the US, present works for the modeling and the analysis of the intraday interest rate. However, their econometric models are still based on a linear regression. That means that their estimates of the term structure of interest rates are locally linear even though they indicate some nonlinear intraday term structure.

Based on their argumentation and in our opinion, it is quite intuitive to assume that this SIYC is a nonlinear function in maturities, which can be modeled by the NSM. Hence, the capability of the NSM to model the SIYC lies within the research focus of this paper.

After providing the method to analyze the intraday SIYC on an interbank credit market, the second core research objective is to analyze the effects on the interbank credit market before, during and after the financial crisis of 2007. To analyze these effects, we split the data into four periods and redo the same analysis for each period separately.[5]

The estimated intraday SIYC-s show a dramatic change in the intraday dynamics during the turmoil, whereas, prior to this turmoil, the intraday dynamics had been quite flat, signaling that the interest rate was not expected to change significantly during the day. After the last intervention of the ECB in the sample on the 13th of May 2009, the dynamics of the intraday interest

[5] Fecht and Reitz (2012) claim that there is a bias in the e-MID data after the outbreak of the financial crisis in 2007 due to the fact that many international banks left the market. This problem is not relevant to this paper as we only use transactions between Italian banks (see next chapters).

rates become almost flat again. This can be seen as a result of the disappearance of liquidity in consequence of the provision of cheap and almost riskless liquidity through the ECB.

In this context, we do the analysis of the empirical fit of the model to evaluate its empirical relevance for the modeling of the intraday yield curves. To our best knowledge, our analysis presents the first estimation of the yield curve on the intraday frequency for the e-MID using the nonlinear NSM.[6] As already mentioned, the further goal of our paper is to find out whether the differences in the estimates of the SIYC-s for the different periods with focus on the financial crisis are statistically relevant. Significant differences in the model fit can detect systematic differences in the behavior of the market participants and thus, provide the evidence of the state of the market signaling for a possible financial crisis. To this end, we will use the NSM for the analysis of SIYC in the e-MID based on observable intraday interest rates due to the model's theoretical and practical importance and simplicity.

Lastly, we do this analysis in the light of very practical purposes. This is, to let our analysis and results serve for practical uses, such as the direct estimation and forecast of the intraday interest rates on the interbank credit market at high frequencies for tick-by-tick data.[7]

This paper is organized as follows: In chapter 1.2, we briefly introduce the e- MID market. In chapter 1.3, we postulate our working hypotheses. In chapter 1.4, we present the NSM and the estimation technique which we apply. In chapter 1.5, our data set is presented along with the descriptive statistics for the estimation of the SIYC-s. The statistical evaluations of our estimates are presented in chapter 1.6. In chapter 1.7, we interpret the estimated yield curves from an economic point of view. Additionally, we present implications of our estimated SIYC-s in chapter 1.8. In chapter 1.9, we conclude our paper.

[6] And for an interbank credit market in general.

[7] Moreover, our results can help to optimize the trading strategies on the interbank credit market as well.

1.2 The e-MID

The e-MID was founded in 1990 as an initiative of the Bank of Italy. Initially, the e-MID was used exclusively for the euro interbank market. However, its activities expanded rapidly into other currencies, including the U.S. dollar, the British pound, and the Polish zloty (Brunetti et al., 2010).

The trading volume and number of transactions increased systematically in the e-MID until the outbreak of the global financial crisis. Before the crisis, on any dealing day, about 450 transactions were completed with an average credit volume of 5.5 million euros per transaction (Gabbi et al., 2012).

The trading period in the e-MID begins daily at 08:00 AM and ends at 06:00 PM (UTC+1). During this period, credits ranging from a minimum amount of 50,000 euros and a maturity of one day to credits with a maturity of up to one year are traded. As already stated, the segment of overnight credits represents about 90% of all transactions, in terms of both absolute number of transactions and trading volume, in general as well as in our sample.

Various lending institutions, including banks and investment companies, are allowed to actively participate in the e-MID. To do so, these institutions must meet several requirements: The net capital of credit institutions, including banks, must be a minimum of $10 million U.S. or its equivalent in another currency, and for investment companies it must be 300 million euros or its equivalent in another currency. Before the outbreak of the global financial crisis in 2007, 246 institutions from 29 countries of the European Union and the United States were members of the e-MID. Among them were 30 central banks and two finance ministries, which worked as market observers, and 108 domestic (Italian) and 106 international banks as active market participants (Gabbi et al., 2012).[8]

The functioning of the e-MID can be described as simple and transparent. The bank acting as quoter establishes the credit inquiries, both lending and borrowing credit orders, in the order book of the e-MID, which can be monitored by all market participants in real time. The identity of the quoter bank and the credit amount, the interest rate, the credit term, and type of credit application (credit borrowing or credit lending) are revealed. If the order is a lending order, the quoter bank shows a cash surplus. If it is a borrowing order, the quoter bank reveals a liquidity demand. The bank that operates as an aggressor has the option of choosing a credit request from

[8] For a detailed description and explanation of e-MID see: Gabbi et al., 2012, Brossard and Saroyan, 2016.

the order book and arranging a credit. After the aggressor bank identifies a credit request from the order book as appropriate, the credit transaction is nearing completion. The e-MID system again allows both market participants to negotiate the specifications of the credit. Furthermore, the quoter bank has the right to reject the lending order, while the aggressor has the right to abort the order once the counterparty is known. If the transaction is executed, it is automatically processed by the payment system and the order book is automatically updated (Iori et al., 2012, Brunetti et al., 2010).

This market mechanism is a peculiarity of the e-MID and offers an important advantage over other interbank credit markets: the market can be described as completely transparent and reliable, with the possibility for all market participants to monitor the trading and the interest rate developments in real time (Iori et al., 2012, Brunetti et al., 2010).

However, the complete transparency of the e-MID may also be a pitfall, especially during times of a financial crisis. Because times of turmoil are marked by a high degree of uncertainty about bank liquidity, many banks avoid trading in transparent markets in order to hide potential liquidity shortfalls. This complete transparency could explain the phenomenon that the volume and number of transactions and the number of active market participants in the e-MID decreased steadily after the onset of the financial crisis in 2007 (Iori et al., 2012).

1.3 Working hypotheses

Baglioni and Monticini (2008) claim that the intraday yield curve shows a clear downward pattern throughout the operating day in 2003, 2004, and afterwards in 2007, especially after the outbreak of the financial crisis in August (see Baglioni and Monticini, 2010). The objects of their interest are credits with shorter maturity than one day on the e-MID. The authors claim that there is an implicit intraday interest rate whenever the overnight interest rates differ within an operating day and depending on the intraday time point at which the overnight credit contract was traded. Their analysis and results support the assumption that the intraday interest rate shows a clear downward pattern during a trading day. This is explained by the theoretical assumption of the risk premium within intraday credits and the cost of borrowing from the central bank in 2007 (Baglioni and Monticini, 2010). However, the e-MID belongs to the class of electronically organized financial markets where the price process is mainly influenced by the unobserved process of incoming news.

Affinito (2012) suggests that in times of financial stability banks select their counter partners based on observable as well as testable monitoring factors, including different credit ratings.

This selecting mechanism changes in times of a financial turmoil. After the outbreak of the financial crisis in August 2007, the borrowing banks are selected mainly based on preexisting relationships and non-observable risk indicators. Moreover, Angelini (2008) finds out that, when the central bank announces a rate change, the market reacts and revises the expectations about the overnight rate. Furthermore, he suggests that the overnight rate can be changed not only by the central bank but also by other macroeconomic news. Baglioni and Monticini (2013) also argue that the differences in the intraday interest rate, which become more relevant after August 2007 and after September 2008, may be interpreted also by the changes of the spread between the EURIBOR and EONIA rates, reflecting incoming news. Hence, we will assume that the price building process on the e-MID is also driven by incoming relevant news, as it is the case on every financial market.

In this context, the efficient market hypothesis of Fama (1970) postulates that the movements of financial prices essentially depend on a 'news arrival process' whereby incoming news are immediately incorporated into the asset prices in an unbiased way. Several empirical works provide the evidence that news of monetary variables (Pearce and Roley, 1983, Hakkio and Pearce, 1985) and of real economic variables (McQueen and Roley, 1993, Birz and Lott, 2011) are relevant in the price building process of asset prices.

The evidence of the relevant impact of news on the volatility of stock prices is overwhelming, while the impact of bad news should be even stronger (e.g. Engle and Ng, 1993, Bomfim, 2003, Brenner et al. 2009).[9] Hanousek et al. (2009) provide the evidence of spillovers caused by news through different markets while Plummer and Tse (1999) and Caporale et al. (2014) show that volatility-spillovers with bad news have a greater impact than the ones caused by good news. Caporale et al. (2014) base their analysis on newspaper coverage of macro news on stock returns and find out that positive (negative) news have significant positive (negative) effects on stock returns, while the volatility of news has a significant impact on both stock returns and volatility. These effects are shown to be stronger during the financial crisis.

These effects of news on prices and volatilities are more obvious in case of intraday data (Rigobon and Sack, 2003, Rangel, 2011). In general, bad news increase the volatility more than good news. Those analyses show that the strong nonlinear price process on financial markets is caused by news processes what we can also assume for the interest rate process on the interbank

[9] However, the condition is that the news are somehow unknown or to some extent not anticipated at the time the news arrive.

credit market. That means that the assumption of an only monotone falling intraday interest rate is very restrictive and that one should also consider any kind of nonlinear intraday patterns.

Thus, based on the impact of news in the e-MID and the evidence of spill-overs through financial markets, our first working hypothesis is:

H1: The nonlinear Nelson-Siegel-model is feasible for modeling and estimating the SIYC.

Moreover, Kleinnijenhuis et al. (2013) state that during a financial crisis, the high-frequency trading and high-frequency sentiment analysis is very sensible vis-à-vis much more intensive, dramatic and frequent news processes. Therefore, one can assume that there are different states of the markets, or the e-MID in this case. Thus, under the assumption that the more frequent and relevant news during a financial crisis hit the market, our second working hypothesis is:

H2: During the financial crisis, the usage of the NSM for modeling and analyzing the SIYC becomes even more feasible.

1.4 The NSM and the estimation

As already stated, modeling the yield curve has been of high interest in the last years. One of the first models that experienced wide use in practice is the NSM. This model was extended and improved in several works (e.g., by Svensson, 1994, Diebold and Li, 2006), which present relevant models for the yield curve as well. However, as already stated, we use this basic model due to its simplicity and proven empirical performance.
Nelson and Siegel (1987) assume that the forward rate, here denoted as *r*, can be represented by the solution of the following differential equation:

$$r(m) = \beta_o + \beta_1 e^{\left(\frac{-m}{\tau 1}\right)} + \beta_2 \mathrm{e}^{\left(\frac{-m}{\tau 2}\right)} \quad (1.1)$$

Where *m* denotes the maturity of the credit. β_0, $\beta_{1,}$ β_2 are parameters determined by the initial conditions, τ_1 and τ_2 are time constraints associated with the equation. This equation generates a wide range of forward rate curves that take, depending on the value of parameters β_1 and β_2, a monotonous form, a hump with the positive or negative sign, or an S-shape.
The yield to maturity on a specific contract, referred to as *R(m)*, is the average of the forward rate curves and is calculated by the following formula (Nelson and Siegel, 1987):

$$R(m) = \frac{1}{m}\int_0^m r(x)dx \quad (1.2)$$

In this case, the yield curve, which is implied by the model, has the same range of forms. Nelson and Siegel (1987) concluded that this model is over-parameterized and does not converge numerically. They developed a new model that can model empirical yield curves. This model can be represented by the following differential equation:

$$r(m) = \beta_0 + \beta_1 e^{\frac{-m}{\tau}} + \beta_2 \frac{m}{\tau} e^{\frac{-m}{\tau}} \qquad (1.3)$$

Where β_0, β_1, β_2 specify the parameters to be estimated and τ denotes the time constant. For a given τ, this model is linear. The forward rate of model (2.3) includes three terms and is thus modeled by three parameters. The parameter β_0 represents a constant. The second component, $\beta_1 e^{\frac{-m}{\tau}}$, represents an exponential term which changes monotonically with increasing duration to zero. If β_1 is negative, this term increases monotonically, and vice versa. The last component, $\beta_2 \frac{m}{\tau} e^{\frac{-m}{\tau}}$, is responsible for the modeling of a positive or negative hump in the yield curve. This term can cause U-shaped yield curves as well. If the maturity *m* takes high values and strives toward infinity, then the value of the function *r(m)* approaches the value β_0. However, when the maturity approaches zero, then the function value approaches the value $\beta_0 + \beta_1$ (Hewicker and Cremers, 2011).

To represent the yield as a function of maturity, Nelson and Siegel (1987) propose integrating model (1.3) from zero to *m* and then dividing by *m*. The result of this process is the following equation, which is the linear function by given τ (Nelson and Siegel (1987):

$$R(m) = \beta_0 + \beta_1 \frac{1-e^{\frac{-m}{\tau}}}{\frac{m}{\tau}} + \beta_2 \left(\frac{1-e^{\frac{-m}{\tau}}}{\frac{m}{\tau}} - e^{\frac{-m}{\tau}} \right) \qquad (1.4)$$

The limit of the function *R(m)* is equal to β_0 if the maturity *m* takes high values and is equal to $\beta_0 + \beta_1$ if the maturity *m* takes low values, which are the same for the forward rate in model (1.1), since *R(m)* represents only the average of *R(m)* (Nelson and Siegel ,1987).

Another possibility, according to Nelson and Siegel (1987), is to detect whether the flexibility of the curves of model (1.1) reflects the interpretation of the coefficients β_0, β_1, and β_2, and thus the influence of the short-, medium-, and long-term component of the spot rate curve for an explanation of the yield curve.[10]

Nelson and Siegel (1987) showed that a variety of empirical yield curves can be modeled based on this model.

Using the MATLAB software, the parameters of the NSM for the SIYC-s were estimated based on formula (1.4). This is done by the numerical optimization applying an objective function over τ, whereas the parameters β_0, β_1, and β_2 are estimated simultaneously in each optimization step using ordinary least squares (OLS). For these purposes, the optimization function "fminbnd" is chosen with the default settings. The "fminbnd" function requires the specification of interval boundaries within which the optimal value is sought for τ. In the context of this paper, the interval limits are set in the range of 0 to 10000.

To estimate the SIYC-s using the NSM, it is first necessary to define the maturity of each credit. For this purpose, we suggest a new concept of intraday maturity, which has not been used by other researchers until now to the best of our knowledge. The maturity of each overnight credit in the interbank credit market is calculated by the following formula:

$$m(i) = \big(18 - T(i)\big) + a \qquad (1.5)$$

where *m(i)* refers to the maturity of each credit *i* (measured in hours).

The number 18 represents the time point (06:00 PM) when the e-MID closes on every trading day. After this time, no further credit transactions on the day are allowed. *T(i)* refers to the time at which a credit is assigned.

The market opens on each trading day at 08:00 AM. If an Italian bank is involved in a credit transaction, the overnight credit must be repaid on the following day at 09:00 AM. If no Italian bank is involved in the credit transaction, the time of credit repayment is 12:00 PM. Thus, a in equation (1.5) equals one and four in the first and second case respectively.

[10] For more details about modeling different shapes of yield curves and the particular role of each parameter, see Nelson and Siegel (1987).

1.5 Data and descriptive statistics

In our sample, the credits borrowed by the Italian banks represent about 91% of the total credits. Italian banks also represent the majority of active borrower banks. In addition, many international banks are not active over longer periods in the e-MID. Furthermore, our calculations show that about 96% of the credits borrowed by Italian banks are also provided by Italian banks (330,078 of 344,445 credits). The remaining 4% of the credits, taken from foreign banks, can be regarded as noise. Because of these conditions, the SIYC-s were estimated for overnight credits valued between Italian banks. Many other studies e.g. Hatzopoulos et al. (2015) and Iori et al. (2015) also focus only on transactions between Italian banks.

This implies that the repayment time of each credit extends for one hour because only credits between Italian banks are considered to estimate the intraday yield curve. So, a =1 in equation (1.5) for all transactions in this paper.

A further restriction of the estimation of the yield curve, which was taken in the context of this paper, relates to the maturity of the respective credits. All credits with a maturity of less than two hours were excluded. Thus, the credits taken up after 05:00 PM have not been considered in the estimation. This is because in the period of borrowing from 05:00 PM to 06:00 PM, a relatively small number of credit transactions is observed. Additionally, Gürkaynak et al. (2007) point out that the yield curves behave oddly and should not be estimated based on securities with a very short maturity. This stylized fact is observed due to the lower liquidity of such securities. This is exactly the case in our data set that we observe after 05:00 PM until 06:00 PM. Thus, we estimate the SIYC-s for the maturities in the interval between 08:00 AM and 05:00 PM. The number of credits included in our estimation is about 99.1 % (327,281 out of 330,078 observations). After all restrictions are considered, the SIYC-s are estimated for overnight credits between Italian banks with a maturity of two (minimum maturity) to eleven hours (maximum maturity).

According to Hatzopoulos and Iori (2012), banks on the e-MID behave differently in the precrisis period and during the period of the financial distress. We mainly adopt the argument of Gabbi et al. (2012) for the recognition of the key time points in our data sample, which allows us to define four relevant time periods with different economic states on the e-MID.

The first period starts on 03.10.2005 and ends on 08.08.2007, one day before the onset of the global financial crisis, which was caused by disturbances in interbank lending (Green, 2011). The second period starts on 09.08.2007, on the onset of the financial crisis and ends on 14.09.2008 (the effective period ends on 12.09.2008, as the next two days are a weekend). The third period starts on 15.09.2008, the day Lehman Brothers collapsed, and ends on 12.05.2009. The fourth and last period starts on 13.05.2009, with the ECB's final reduction of the key interest rate in the observation period, and ends on 31.03.2010.[11] The four periods are shown in Table 1.1.

Table 1.1: Presentation of the sub-periods

Period 1	03.10.2005-08.08.2007	Period before the crisis
Period 2	09.08.2007-14.09.2008	Outbreak of the crisis until the collapse of Lehman Brothers
Period 3	15.09.2008-12.05.2009	Lehman Brothers collapse until reduction of key interest rate
Period 4	13.05.2009- 31.03.2010	Key interest rate reduction until the end of the observation period

The main descriptive statistics for the credit transactions between Italian banks in the sample period are summarized in Tables 1.2-1.5.

Table 1.2: Descriptive statistics: days and observations

	Whole Sample	**Period 1**	**Period 2**	**Period 3**	**Period 4**
Number of days [12]	1,641 (1149)	675 (473)	403 (281)	240 (166)	323 (229)
Transactions	327,281	155,992	87,427	40,483	43,379
Mean of transactions per day	283.607	328.404	311.128	242.413	190.259

[11] In contrast to Gabbi et al. (2012), we construct one more time period after the last ECB intervention.
[12] In parentheses: effective days, excluding weekends and holidays.

Table 1.3: Descriptive statistics: interest rates

	Whole Sample	Period 1	Period 2	Period 3	Period 4
Mean	2.837	3.023	4.037	2.164	0.380
Std. Dev.	1.293	0.649	0.194	1.267	0.197

Table 1.4: Descriptive statistics: volume (in Million Euros)

	Whole Sample	Period 1	Period 2	Period 3	Period 4
Mean volume per day	6,384.313	8,215.736	6,735.380	4,849.408	3,344.431
Mean per Transaction	22.511	25.017	21.468	20.004	17.578

Table 1.5: Descriptive statistics: maturity (in hours)

	Whole Sample	Period 1	Period 2	Period 3	Period 4
Mean	6.906	6.887	6.734	7.221	7.030
Std. Dev.	2.576	2.618	2.571	2.471	2.497

As we can see, the mean of intraday interest rates, the mean volume per day and the mean volume per transaction drop enormously after the collapse of Lehman Brothers.

This period is seen as the culmination of the financial crisis, where the crisis became even more acute (Lane, 2012). This trend is also observable in period 4. Hence we can state that our periods 3 and 4 are associated with (and after) the culmination of the financial crisis and its consequences for the interbank credit market, respectively. This fact leads to the conclusion that the system experienced a dramatic change in these two periods compared with the previous two ones. We thus claim that the system changes its state. During these particular periods, the maturity of the credits increases as well compared with periods 1 and 2. Furthermore we can observe an increase of the average maturity. That mean that the traders seem now to become more active earlier within a day. That can be due to the lower trading volume and the lower number of trades in periods 3 and 4, and thus to the higher risk in the market. To sum up, periods 1 and 2 refer to the normal state of the e-MID, whereas periods 3 and 4 are recognized as an abnormal state of the market, where the liquidity provision is no longer working properly anymore.

1.6 Statistical evaluation of the estimates

We apply the NSM by estimating its parameters and calculating R^2 for each single day. Hence, the number of R^2-s is equal to the number of days in our data sample. Table 1.6 presents the descriptive statistics for the estimated R^2 in the whole sample and for each period. At first, we can state that the goodness-of-fit of the NSM in the empirical estimation of the SIYC-s on the e-MID is quite high. We report an average R^2 of 0.3565 in the overall sample. Moreover, based on the t-statistics, R^2 seems to be statistically different from zero at the 1% significance level in the whole sample as well as in each period.[13] Thus, with respect to our first working hypothesis, we can confirm that the NSM is suitable for the modeling of the SIYC-s on the e-MID.

Table 1.6: Descriptive statistics for R^2 for the SIYC-s estimated by the NSM

	Whole sample	**Period 1**	**Period 2**	**Period 3**	**Period 4**
Mean	0.3565***	0.3709***	0.4242***	0.3185***	0.2714***
Std. dev.	0.2049	0.2065	0.2150	0.1920	0.1603
t- statistic	58.8924	39.0626	33.0735	21.3747	25.6197

*** Denotes significance at the 1% level.

In the pre-crisis period, an R^2 of 0.3709 is achieved, which is also significant at the 1% significance level. In this period the dynamics of the intraday interest rates are mainly influenced by the intraday risk premium, as already stated by Angelini (2000) or Baglioni and Monticini (2008). However, this R^2 is much higher than the R^2 achieved by both Angelini (2000) and Baglioni and Monticini (2008), of 0.02 and 0.09 respectively, in their analysis for the pre-crisis period.[14]

[13] Given a quite high number of observations, we can apply the t-test for these purposes due to asymptotic properties of the t-test.

[14] However, in both articles authors use the hourly averages of interest rates on e-MID as the dependent variable, whereas we use the original tick-by-tick interest rates. From a practical point of view, that means that our results are even more interesting for the analysis and the practical use of the SIYC, e.g. for the trading strategies.

Period 2 is characterized with the highest average R^2 of 0.4242. The average of the R^2 is also here statistically different from zero at the 1 % significance level. This is the period after the onset of the financial crisis. Given the highest average R^2, compared with the other periods, indicates that the NSM has the best goodness-of-fit in this particular period. We interpret this empirical result such that the traders in this first period of the financial crisis are influenced by the significant, relevant and more frequently incoming news and are thus forced to systematically and more frequently update their intraday trading strategies. The average R^2 is also quite higher than the average R^2 provided by Baglioni and Monticini (2010), of 0.34 from July 11th to August 6th and of 0.21 from August 8th to September 10th, who also state that after the outbreak of the financial crisis the intraday interest rate structure becomes more important and not quite flat like before.

In period 3, the R^2 decreases to 0.3185 but remains significant at the 1% level. After the collapse of Lehman Brothers at the beginning of period 3, traders begin to successively escape the e-MID and the market mechanism appears not to function properly anymore. Thus, our previously described change of the state of the market can also be observed by considering the R^2. Porzio et al. (2009) state that after the outbreak of the financial crisis, abnormal patterns of volumes and interest rates can be identified on the e-MID. They can only be described as the worries about the quality and the quantity of the liquidity in the market or the much higher degree of counterparty risk. Furthermore, the behavior on the e-MID differs from the law of supply and demand so that the lower rate may not immediately mean higher demand in this period. This can be explained by the fact that many lender banks left the market (to other interbank credit markets or hoarded their liquidity), which leads to a high lack in supply for interbank credits on the e-MID (Porzio et al., 2009). In our opinion, this is the reason why the estimated R^2 in this period is lower than in the second period.

In period 4, whereas the market differs even more from its normal state, the R^2 decreases further but is still statistically different from zero at the 1% significance level. At the beginning of this period, the ECB reduces the key interest rate for the last time in the sample period. The ECB has taken over the liquidity provision for the banks. As already pointed out by Gürkaynak et al. (2007), the interest rates and yield curves behave oddly in times of low liquidity. Therefore, we identify this as the reason why the NSM performs in the last period of our data sample not as well as in the previous periods in terms of R^2.

Summing up for the whole sample and for all sub periods, we achieve a remarkable high and at 1% statistically significant R^2. Therefore, we cannot reject our first hypothesis.

Furthermore, we can state, that these differences in the R^2 are also statistically different from zero at the 1 % significant level. This is confirmed by the results in table 1.7 for the two sample t-test.

Table 1.7: Two sample t- test of R^2 for the SIYC-s estimated by the NSM

	Period 2	**Period 3**	**Period 4**
Period 1	-3.3732***	2.8710***	6.4037***
Period 2		5.2291***	8.9013***
Period 3			2.6497***

***Denotes significant different means at the 1%.

Regarding our second hypothesis, we can state that the lowest goodness-of-fit is found in period 4 and the best one in period 2; the results of the two sample t-test confirms this finding. Thus, the highest likelihood for the correct modeling of the SIYC dynamics via the NSM is in the appearance of the financial crisis as long as the market mechanism may still be intact. In our opinion, the process of more frequent and important incoming news within a day after the onset of the financial crisis causes a stronger systematic impact in the SIYC resulting in the highest R^2 of the NSM. The second highest R^2 is found in period 1 where the market is also in the normal state.

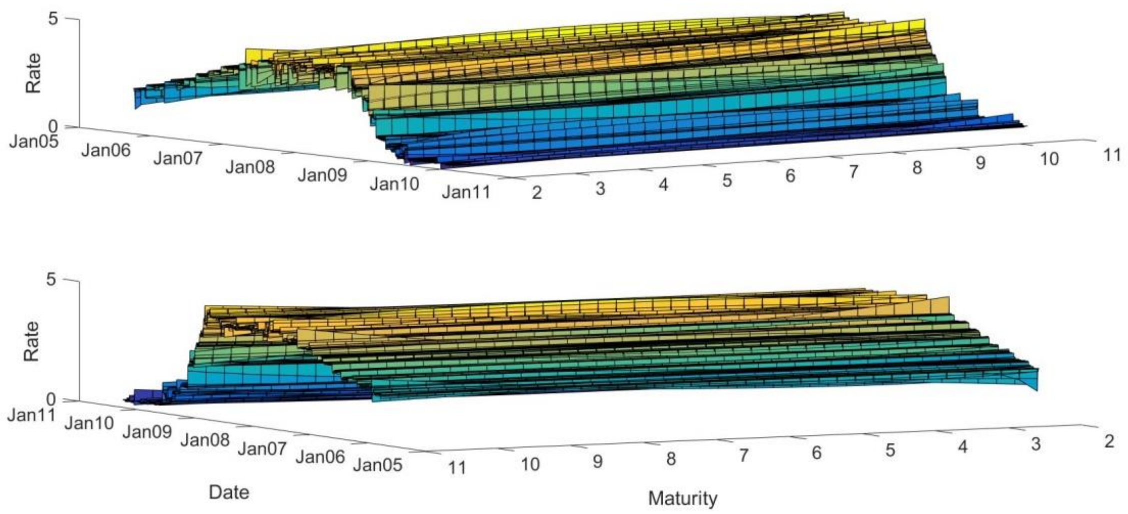
In period 3 and 4, the market is in abnormal state with the successively withdrawn liquidity, which turns into a significantly lower R^2 compared with periods 1 and 2. However, our results from period 1 (outside the crisis) and period 3 (within the crisis) may not be directly compared with each other due to the different states of the market. Therefore, we can neither reject nor confirm our second hypothesis regarding period 3. This is also the case for period 4, with the worst results regarding R^2. Based on this fact, it can be reasonably expected that the goodness-of-fit of NSM will be worst when the market does not function properly. Given a well working market in the financial crisis, the NSM achieves the highest goodness-of-fit. This is stated through our second hypothesis what means in turn that our second hypothesis cannot be re-jected.

1.7 Graphical presentation and economic interpretation of the estimated SIYC-s

To illustrate the effects on the SIYC-s visually, we provide the graphical presentations of the estimated curves in this chapter.

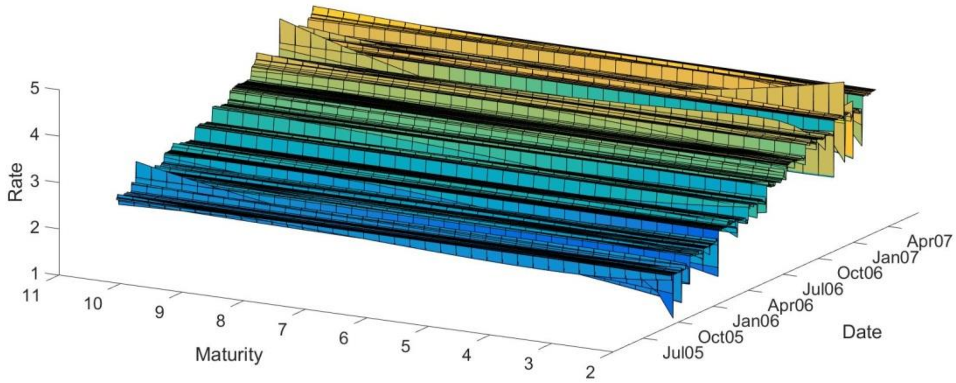
The estimated SIYC for each trading day and for the entire sample are shown from two angles in Figure 1.1. One can see flat yield curves before the turmoil; followed mostly by quite different and highly nonlinear yield curves until they become flat again at the end of the considered sample period when the ECB takes over the role of the liquidity provider for the e-MID.

Figure 1.1: SIYC-s in the whole sample



The first period under consideration in the e-MID is characterized by a high degree of liquidity. The volume and number of credits between Italian banks are increasing. Also, the number of active banks increases during this period. This implies a high degree of confidence in the likelihood of repayment between the Italian banks. Most of the SIYC-s are flat with some small positive and negative intraday tendency. Moreover, on the daily frequency, the daily interest rate follows a positive trend from about 2% at the beginning of this period to about 4% at the end. The SIYC-s for the first period are shown in Figure 1.2.

Figure 1.2: SIYC-s of the e-MID in period 1



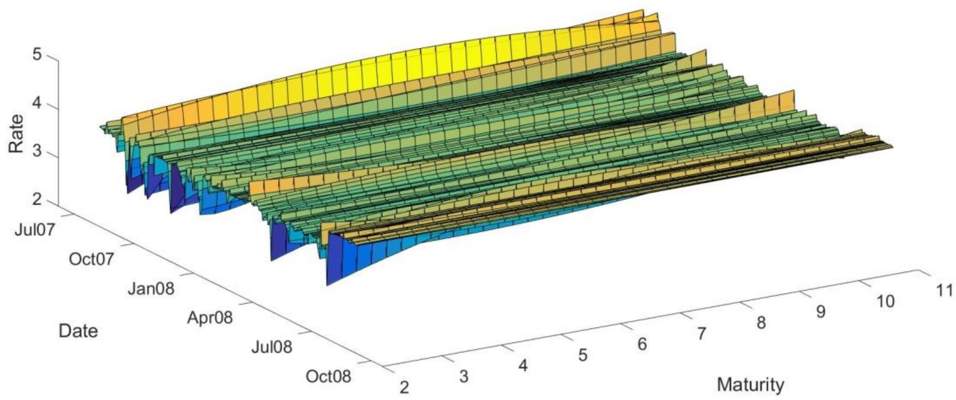
The SIYC-s, with a few exceptions in this period, are quite flat. This implies stable expectations on the intraday frequency in the e-MID that may be caused by a stable global economic development. These findings are also consistent with the findings from Angelini (2000), Baglioni and Monticini (2008) and Gabbit et al. (2012), as we consider a “pre-crisis period”.

From the end of January 2007 to approximately mid-February 2007, non-flat and rather monotone decreasing SIYC-s can be recognized. The borrowing in early stages of a day (long maturity) is predominantly characterized by a higher interest rate than credits taken in a late stage of the trading day (short maturity). These effects in dynamics of the SIYC-s may be the first sign of higher uncertainties on the intraday basis and may thus be an indicator for a possible upcoming financial turmoil.[15] One can explain it as follows: To calculate the risk of lending, at the beginning of the trading day banks demand higher interest rates for the allocation of a credit. The credit risk is a within-one-day calculation and is higher at the beginning of the day due to higher uncertainties. On the other side, if a credit transaction takes place at a later point in time during the day, the amount of uncertainty for that particular overnight credit is lower and the interest rate decreases: thus, the higher the risk, the higher the intraday interest rate (the risk premium as pointed out by Baglioni and Monticini, 2008). However, if some unexpected or new uncertainty, e.g., in form of news, is recognized during the day, traders take this into account for their trading strategy. This can result in a monotone decreasing, increasing or a positive or negative hump in the SIYC. Though, these cases are rarely observed only at the end of this period.

[15] However, this ability of the SIYC-s is not the topic of this research paper and will be left for further research.

Period 2 is characterized by a high volatility of daily interest rates. The interest rates vary widely between 3.7% and 4.4%. In this period, the beginning of a decrease in the volume and number of credits is observed. The shape of the SIYC-s in this period is characterized by different dynamics which reflect a high degree of uncertainty regarding the expectations of Italian banks. The SIYC-s for the second period are shown in Figure 1.3.

Figure 1.3: SIYC-s of the e-MID in period 2



After the outbreak of the financial crisis on the 9th of August 2007, considering higher uncertainties, the creditor banks could not clearly assess within a day the probability of repayment by the borrower banks. There is, therefore, a loss of confidence between banks in the e-MID (see the report by Swiss National Bank, 2008). This loss of confidence is likely to be the cause of the slight decline in the volume and number of loans (Porzio et al., 2009). This phenomenon constitutes a major problem for banks, which depend on interbank credits in this period. The decline in liquidity in the market thus made it more difficult to compensate for liquidity constraints and to achieve the individual investment goals (Cappelletti et al., 2011).

Thus, after the outbreak of the financial crisis, further highly nonlinear dynamics in the estimated SIYC-s are clearly visible in our estimates. The high frequency and the quantity of relevant news during this first period of the financial crisis causes these upward and downward sloping SIYC-s and SIYC-s with positive and negative humps alternate quickly over the days. That means that the expectations were highly unstable and diffuse due to the turmoil in the e-MID.

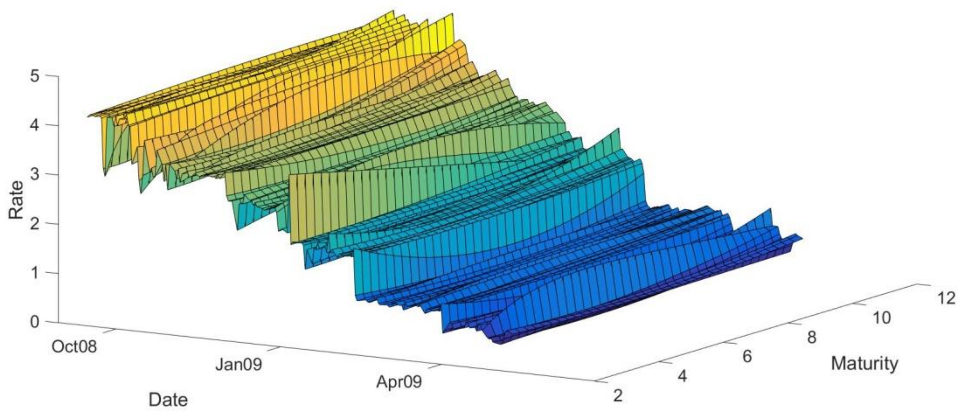
According to the estimates of the SIYC-s, period 2 is the period with higher risk,[16] which is shown in quickly alternating intraday dynamics. Furthermore, as stated by Baglioni and Monticini (2010), the uncertainty about the availability of funds in the interbank market grew substantially. That means that, e.g., credits with longer maturity are offered at a higher interest rate than credits with shorter maturity during a day. Moreover, periods with positive or negative humps were observed as well where participants on the e-MID formed different expectations for the beginning and the end of day compared with the middle of the day, respectively.

On the other side Brunetti et al. (2010) state that, in contrast to the pre-crisis period, where the short-term ECB policies provide liquidity, the unconventional ECB interventions during the financial crisis seem to increase the volatility and the uncertainty in the e-MID market during this period.[17] This phenomenon can also be observed in our estimates in form of alternating nonlinear estimated SIYC-s. After that, the ECB raised the key interest rate for the euro zone in July 2008 to ensure that prices remained stable (Ruckriegel, 2011).
Period 3 starts with the collapse of Lehman Brothers. The estimated SIYC-s for the third period are shown in Figure 1.4. As already stated, this period after the collapse of Lehman Brothers is seen as the culmination of the financial crisis with the highest degree of uncertainty. Thus, the same reasons as in the previous period cause the highly nonlinear alternating forms of the SIYC-s. However, this period is also characterized by the dramatic fall in volume and number of trades on the e-MID. As already mentioned, we assume that the e-MID had entered another state by now. The further consequence is the abrupt negative trend in the interest rate on a daily basis.

[16] Compared with period 1.

[17] E.g., on the 9th of August 2007, where the ECB increased the scope of its main refinancing operations by 95 billion euro (Mojon, 2010).

Figure 1.4:SIYC-s of the e-MID in period 3



The shapes of the estimated SIYC-s in combination with falling interest rates on the daily frequency can be interpreted in two ways: It may reflect a high degree of uncertainty and negative expectations of the Italian banks in the e-MID, also due to developments in the worldwide financial markets. The bankruptcy of Lehman Brothers led to expectations that a similar loss could also occur among banks in the e-MID. Hence due to this uncertainty, we can see in the days after the Lehman Brothers collapse that the SIYC-s have different nonlinear shapes paired with a negative tendency of interest rates on a daily frequency. Baglioni and Monticini (2013) and Gabbi et al. (2012) report a dramatic decreasing intraday interest rate after the collapse of Lehman Brothers (higher interest at the beginning of the day). However, our results show that also days with decreasing and increasing intraday interest rates, or positive or negative humps in the estimated SIYC-s, can again be observed, like in period 2.[18]

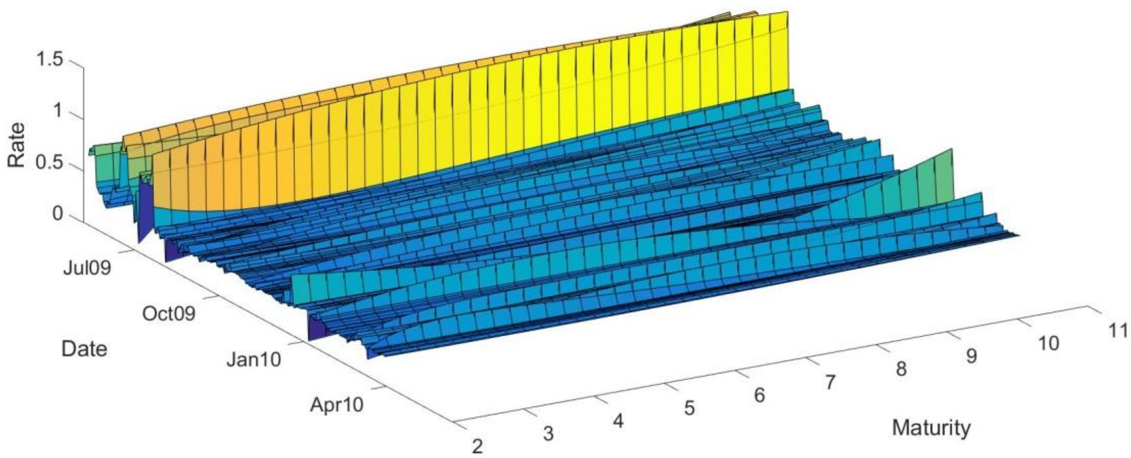
During this period, the interest rate follows a negative trend on a daily basis from about 4.3% at the beginning of this period to a level of about 0.5% by the end of the period. However, this declining interest rate on daily frequency does not imply a decrease in the risk of the granted credits. From our point of view, the opposite was the case. The lender banks could estimate the probability of repayment by the borrowing counter partner only to a very limited extent. The banks were further concerned that systemic risks could lead to contagion (Fricke and Lux, 2015). Thus, there was also a high loss of confidence among Italian banks. In this period, even

[18] Actually, during the whole period we can observe a lot of days where the SIYC has a positive or negative hump in the estimates of the SIYC, e.g., approximately from the end of October 2008 until the end of November 2008 and from the middle of October 2009 until the middle of December 2009.

more banks leave the market and the volume and the number of trades drops significantly (Cappelletti et al., 2011). Banks may invest their cash surpluses in other markets, to deposit them with the ECB at the deposit rate, or to hoard them. This resulted in a massive decline in the volume and number of credits.

The fourth and last period starts on 13.05.2009 with the last ECB intervention in the sample period and ends on 31.03.2010 in our sample. The estimated SIYC-s for the fourth period are shown in Figure 1.5. As we can see, after the last key interest rate change during the observation period, the interest rate increased for a short period from about 0.5% to 1%. This implied a slight gain in confidence of Italian banks and caused a short-term increase in the volume and number of credit transactions between Italian banks. This trust-gain, however, was not of great duration. This in turn resulted again in highly nonlinear dynamics in the SIYC-s over subintervals.

Figure 1.5: SIYC-s of the e-MID in period 4



Also in this period dynamics, with the market still in an abnormal state, SIYC-s show different types of shapes, indicating again diffuse expectations and a different behavior of participating banks in the e-MID with respect to the intraday dynamics of interest rates.

The Italian banks with a cash surplus may either continue to invest more in other markets, to deposit them with the ECB or to hoard them. The banks with a credit need could borrow funds at zero risk at a very low interest rate directly from the ECB. Due to this fact, the number of credit transactions and the volume are on the lowest level and the e-MID becomes less system relevant.

According to Hatzopoulos and Iori (2012), there are two "natural" timescales in the network of the e-MID. The one timescale is set by the maturity of the credit transactions, mostly overnight, and the other one is based on the monthly deposit of minimum liquidity reserves at the central bank, the so-called reserve maintenance period, which is equivalent to one calendar month or around 23 business days. In each reserve maintenance period, the levels of the minimum reserve are calculated based on each bank's balance sheet (Hatzopoulos et al., 2015).

The consequence is that the SIYC has regularities within the meaning of seasonal influences that affect the level of the yield curve. In general, the participants in the e-MID align their activity to these dates. Thus, there are clear monthly seasonal impacts and dynamics caused by these requirements. In our opinion, this is also the reason why the estimated SIYC-s seem to be very erratic over the considered days. In their estimates, Baglioni and Monticini (2013) exclude the last days of the maintenance period due to jumps in the interest rate on these particular days in each month.

Thus, to graphically present the estimated SIYC-s without the seasonal influence, we calculate the smoothed SIYC for each day using a moving average process of 23 days in the entire observation period.
The smoothed SIYC-s are presented in figures A 1.1-A 1.4 in the appendix. So, we can see the before mentioned effects on the SIYC-s even better.

1.8 Implications of the SIYC estimation

After the SIYC was interpreted from an economic perspective in different periods, the question arises whether and what economic implications can be derived based on the SIYC-s from the e-MID.

The first implication relates to the borrowing of overnight credits by Italian banks on the e-MID. The estimated SIYC-s may allow the participants on the e-MID to recognize opportunistic trading strategies in sense to determine the optimal point in time with a low intraday interest rate, or alternatively, to be able to forecast the intraday time with a high intraday interest rate. This is particularly apparent just before and after the outbreak or in the middle of the financial crisis, since highly nonlinear dynamics exist in these times in the SIYC-s for individual days in the e-MID. Through consideration of the estimated SIYC-s, one can see that interest rate differentials of 1% are possible within one day.

Additionally, the ECB can benefit from the consideration of the empirically estimated intraday SIYC as well. Since the interbank credit market is the first transmission channel of monetary policy, the ECB can assess banks' expectations on interbank credit markets and observe the effects of their actions on those markets, like the consequences of a reduction or a rise in the key interest rate. Through such evidence based on the estimated SIYC-s, the ECB may be able to choose the optimal timing of its actions and thus generate the best results regarding this specific interbank credit market.[19]

1.9 Conclusion

The aim of this paper is to propose the concept of the SIYC and its estimation method. The SIYC-s were estimated for the e-MID, a fully transparent interbank credit market using the NSM in the period from 03.10.2005 to 31.03.2010. This estimation of the SIYC on an interbank credit market in this paper presents a novel step in analyzing the SIYC-s.

Our results show that the modeling and estimation of SIYC using the NSM is feasible and attractive. These results can deliver fundamentals for the optimization of trading strategies of participants on the interbank credit market.

At the beginning of the financial crisis until the collapse of Lehman Brothers, the goodness-of-fit of NSM is the highest, and thus, the intraday SIYC-s experience the highest systematic impact. In this time period, the high risk due to the loss of confidence influences significantly the dynamic of the intraday interest rates, as reflected in the highly notable estimates of the SIYC-s. After the collapse of Lehman Brothers and the last ECB intervention, the change of the state of the system occurs, which becomes evident in the light of the lower volume and number of trades. In period 3, the goodness-of-fit becomes lower than in the previous period but remains remarkably high and statistically different from zero at the 1% significance level. This quite abnormal state worsens in the next period after the last ECB intervention (period 4) with the lowest volume and number of trades per day. The consequence is that the goodness-of-fit of the NSM at this point in time is the lowest, but is still statistically different from zero at the 1% significance level.

Our results provide one more interesting finding, namely that shortly before the outbreak of the financial crisis on the 9th of August 2007 and before the Lehman Brothers bankruptcy on the 15th of September 2008, the estimated SIYC-s were indicating different shapes of nonlinear SIYC-s. Such SIYC dynamics may be understood as indicators of an impending crisis in case

[19] For specific suggestions of action for the central banks during the financial crisis see, e.g., Brunetti et al., 2010.

of the normal state of the e-MID. This implication will deserve a more detailed analysis in our future work.

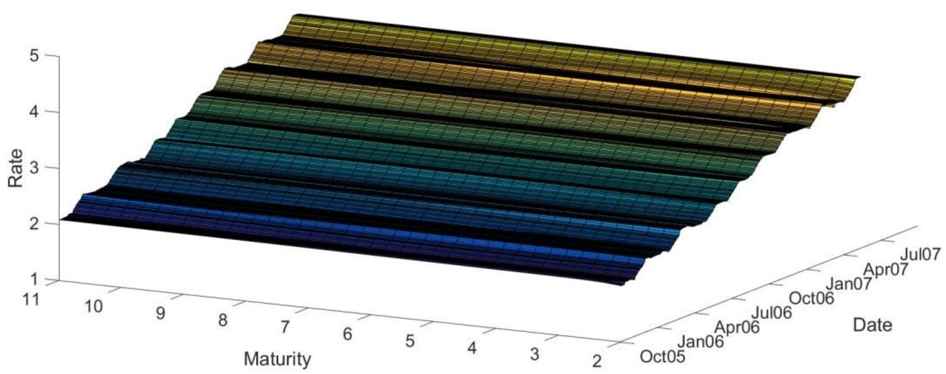
Finally, after 31.03.2010 (sample end) with the outbreak of the European financial crisis in 2010 (Moro, 2014), the ECB took further measures to stabilize the financial system in Europe. These measures included further liquidity provisions. For the e-MID, this had the consequence that the liquidity was successively withdrawn (Barucca and Lillo, 2018). Regarding the ECB's impact, one can expect that the ECB will at some point in time in the future retrovert to its normal state of business and will consequently stop providing cheap liquidity by increasing the leading interest rate. From that time onwards, the e-MID may again become a relevant interbank credit market for the financial system. We thus expect that the NSM will again have a significantly better goodness-of-fit in accordance with these facts.

Our analysis will be extended using other models, such as those presented by Svensson (1994) and Diebold and Li (2006). The goal is to identify the model with the best performance what may be interesting from a practical point of view. This will be our next research focus.

Appendix A: Smoothed estimated SIYC-s

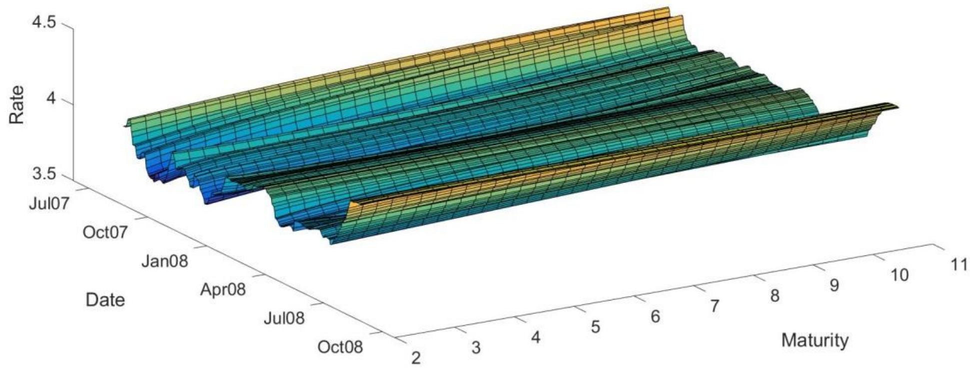
In this appendix, we present the smoothed estimates of the SIYC-s. As already stated, Angelini (2000) and Baglioni and Monticini (2008), Baglioni and Monticini (2010) and Baglioni and Monticini (2013) estimate the intraday yield curve for their whole sample based on hourly averages. From the point of view of the order book analysis, this can actually be seen as the estimation of the intraday seasonality (Hautsch and Jeleskovic, 2008). One usually adjusts the data from the intraday seasonality in the first step to analyze the adjusted data in the second step (Hautsch and Jeleskovic, 2008). Furthermore, the estimates in their analysis is only one regression curve for all days, or for two different periods as in Baglioni and Monticini (2010). The smoothed SIYC-s in this paper may be seen as a kind of a dynamic version of the estimated intraday yield curve, comparable to the results from the previously mentioned studies of Angelini (2000), Baglioni and Monticini (2008), Baglioni and Monticini (2010) and Baglioni and Monticini (2013) due to the fact that the smoothing is done based on the single estimated SIYC-s with a window length of 23 days. That means that we calculate the SIYC over the intraday time points based on the estimated parameters of the NSM for certain maturities. Finally, the smoothed intraday interest rate at each point in time is the average over the 23 estimated intraday interest rates, in the middle of the window respectively. The smoothed estimated SIYC-s are shown for each period in figures A 1.1-A 1.9.

Figure A 1.1: Smoothed SIYC-s of the e-MID in period 1



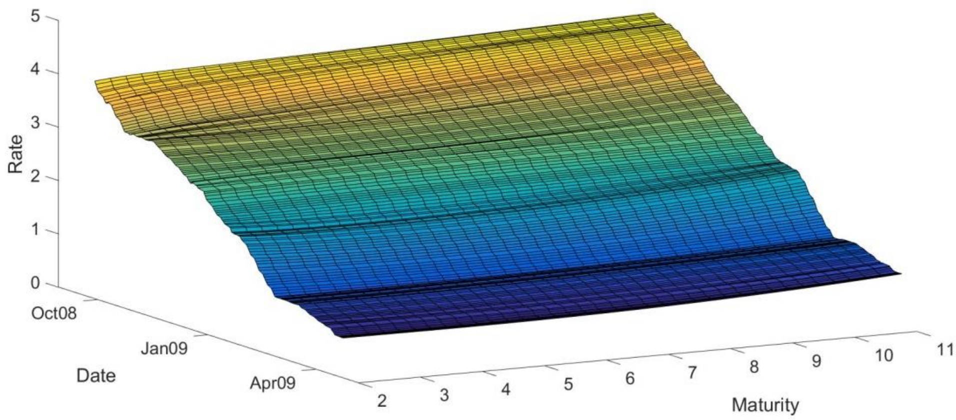
The estimated SIYC-s in period 1 show some negative trend during the day. Credits with a higher maturity are characterized with a higher interest rate and vice versa. As already pointed out by Baglioni and Monticini (2008), this fact relies on the risk premium during the day. This negative trend within a trading day becomes more obvious before the outbreak of the financial crisis during the time between May and August 2007.

Figure A 1.2: Smoothed SIYC-s of the e-MID in period 2



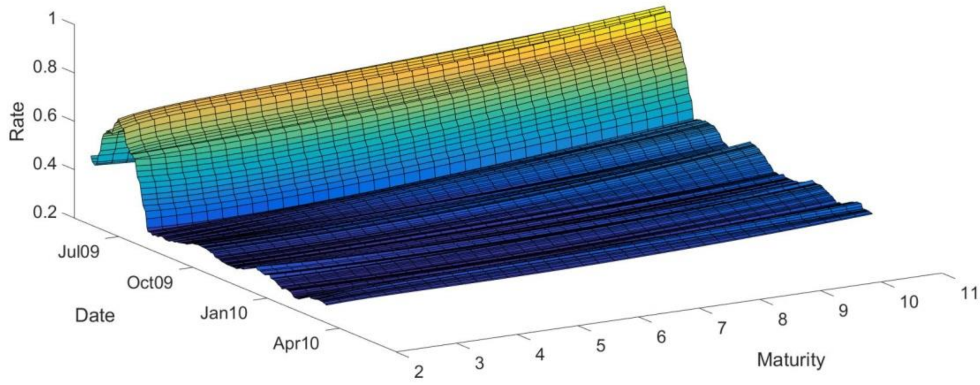
After the outbreak of the financial crisis in August 2007, the dynamics of the estimated SIYC-s change dramatically. In the smoothed SIYC-s we can also see that SIYC-s with a positive or negative trend and a positive and negative U-shape are alternating. This phenomenon is a clear signal of the great uncertainty that hit the market participants in this particular period.

Figure A 1.3: Smoothed SIYC-s of the e-MID in period 3



The estimated SIYC-s in period 3 show clear different dynamics. Between the collapse of Lehman Brothers and October 2008, a clear downward trend is visible. In November 2008, the SIYC-s have a U-shape and are followed SIYC-s with a clear upward trend up to January 2009. After January 2009, the dynamics of the SIYC-s change, again, to a U- shape. After February 2009, we again see some downward trends in the SIYC-s. As already stated, these quickly changing dynamics emphasize the great uncertainty during this period when the financial crisis became more acute.

Figure A 1.4: Smoothed SIYC-s of the e-MID in period 4



After the last intervention of the ECB in the sample period, we see that the interest rate rises from 0.4% to 0.6% for a small time period. During this period, the estimated SIYC show a clear downward trend up to November 2009. After November SIYC with a U- shape are clearly visible.

2. Comparing different methods for the estimation of interbank intraday yield curves

2.1 Introduction

Interbank credit markets play a major role for the distribution of liquidity among banks. On these markets, banks with a liquidity surplus and banks with liquidity needs can efficiently trade and thus optimize their liquidity positions. Distortions on these markets result often in liquidity crunches of banks which then have an effect on the credit supply to households and firms (Affinito, 2012).

Is there an implicit intraday interest on interbank credits? This question has been assessed recently in different papers, due to the fact that changes in the interest rate during the day affect the refinancing costs of banks to a high extend. Jurgilas and Žikeš (2013) and Merrouche and Schanz (2010) in the UK and Furfine (2001 and 2002) in the US, asses this question. By using linear models, they found out that there is a downward trend in the intraday interest rate, meaning that the interest rates in the analyzed interbank credit markets are higher in the morning and lower in the afternoon. In all these studies, authors stress that these results are in line with the theoretical argumentation given by themselves. Abbassi et al. (2017), base their analysis on secured funding data and use a linear model as well. They find out that after the start of the financial crisis, the intraday term structure of interest rates may not be only monotone falling during a day.

Regarding the e-MID market (Mercato Interbancario dei Depositi), the only electronically organized interbank credit in the Euro area and in the US, different studies focus on the estimation of an intraday term structure in different periods. Angelini (2000) was the first one to analyze the intraday behavior of interest rates on the e-MID market. Using a linear model for the intraday interest rates and based on hourly means of the intraday interest rates in the period from July 1993 to December 1996, he finds only very weak evidence for an existing downward intraday term structure.[20] This low evidence is shown in the estimated term structure where the difference of the interest rate in the morning and in the afternoon differs only to a very small degree. Based on his premise, the main force of the intraday interest rates are variations in the market liquidity.

[20] When mentioning a linear model, we refer to a linear regression model.

Baglioni and Monticini (2008), apply also a linear model using hourly means to estimate the intraday term structure in the sample from January 2003 until December 2004. They find weak statistical evidence for a downward trend in the intraday structure which is also reflected in a relatively small difference between interest rate in the morning and in the afternoon. They state that the main drive behind these movements is the higher credit risk, in terms of the counterparty risk, in the morning rather than in the afternoon.

Using two data samples from 11th of July to 10th of September 2007, Baglioni and Monticini (2010) redo their analysis from the year 2008. In this second analysis, they find evidence for a downward trend in the intraday term structure which becomes steeper after the outbreak of the financial crisis in 2007. In addition, here they state that these facts can be observed due to higher credit risk in the morning than in the afternoon.

Baglioni and Monticini (2013) also estimate an intraday term structure on the e-MID market, using three different extended linear models, based on the difference of the average of the interest rates between 09:00 a.m. and 01:00 p.m., called the morning rate, and the average of interest rate between 02:00 p.m. and 06:00 p.m. called the afternoon rate. By using a sample ranging from January 2007 to April 2009 they again find evidence for a downward trend in the term structure of interests. Based on their models this downward trend becomes even steeper after the outbreak of the financial crisis in August 2007 and the steepest after the collapse of Lehman Brothers in September 2008. They also argue that the intraday interest differs from the morning to the afternoon due to higher counterparty credit risk as well as due to market liquidity constraints. Furthermore, they state that the interest rates may be influenced by incoming news in this particular period.

Furthermore, Demertzidis and Jeleskovic (2016) introduced the concept of the spot intraday yield curves (SIYC-s) and differ from the previous studies in two major points, namely the use of tick- by- tick interest rate data and the use of a nonlinear model. For the time period from October 2005 to March 2013, they showed that the SIYC can be modeled and estimated by a standard nonlinear model which is used by many researchers and central banks (Diebold and Rudebusch, 2013), namely by the Nelson-Siegel model (hereafter NSM for Nelson-Siegel model). The authors achieve an R^2 of up to 0.424 on average, which is remarkably high since they use tick-by-tick data. The authors conclude that one should move from the assumption of linear models for the estimation of SIYC towards explicit modelling of the nonlinear dynamics. The second very interesting empirical result is that the goodness-of-fit become significantly higher after the outbreak of the financial crisis. Thus, one should expect higher nonlinear systematic dynamics of yield curves during turmoil on interbank credit markets. The authors attribute this fact to the more intensive process of incoming news within a day during the financial crisis.

The NSM has been modified and extended by many researchers. Among others, Bliss (1996) with his three-factor model interpretation, Björk and Christensen (1999), with their five factor NSM, Christensen et al. (2009) and Christensen et al. (2011) with their arbitrage free interpretation of the NSM and Chen and Niu (2014) with their adaptive dynamic NSM, modified and / or extended the model.

One important model modification which improves the original NSM significantly from the theoretical as well as from a practical point of view is proposed by Svensson (1994) (hereafter SVM for Svensson model). The major highlight of the SVM is modeling a second hump in the yield curve. This model is used for the estimation of the yield curve by many central banks, including the ones of Germany, Norway, Spain, Sweden and Switzerland (BIS, 2005). According to De Pooter (2007), this model should be used when estimations of a larger variety of yield curves or more complex dynamics of the yield curves is necessary. Hence, this model should be used in times of higher volatility, e.g. in times of a financial crisis.[21]

The SVM is also used by many researchers for the estimation of the yield curve for different markets. Among others, Schich (1997) for the German bond market, Clare and Lekkos (2000) for the bond yield curves in the US, Germany and the United Kingdom (UK) and Gürkaynak et al. (2007) for the US bond market, use the SVM for the estimation of the yield curve.[22]

Another popular modification of the NSM is the Diebold and Li (2006) model (hereafter DLM for Diebold- Li model), which also has been used widely in practice and theory. Mönch (2008) e.g. in his study confirms that the model from Diebold and Li provides a good statistical fit for a variety of yield curves.

Among others, Tam and Yu (2008) for the US, the Japanese and the German bond market and Afonso and Martins (2012) for the United States and Germany use the DLM for the estimation

[21] Angelini et al. (2011) state, that interbank credit market rates become more volatile in times of a crisis.

[22] Besides the original NSM, many researchers have modified the SVM as well. E.g. De Rezende and Ferreira (2008), purpose a five-factor model, Christensen et al. (2009) present a dynamic version of the model and De Rezende (2011) presents a six-factor model. However, many of these models are mostly not used from a practical point of view.

of the yield curve. Furthermore, this model is also used from a practical point of view in different studies, e.g. to model and forecast the term structure of futures on oil contracts (GrØnborg and Lunde, 2016).[23] Besides the different studies of yield curve estimations, many analyses focus on the comparison of different yield curve estimation methods. These studies try to, empirically, find out which model suits the best under different conditions and different markets and countries.

Csajbok (1999) compares different estimation methods for the yield curve, including different spline-based methods as well as the NSM and the SVM, for the Hungarian bond market. One of his key findings is, that the SVM is superior to the NSM and different spline-based methods for the estimation in Hungary. This may be because according to Csajbok the SVM is able to capture a more complex variety of yield curves. Ganchev (2009) models and estimates the spot rates for the Bulgarian bond market. In his study he uses different estimation methods including also the NSM and the SVM. One major finding is, that the NSM has a poorer performance than the SVM. Aljinović et al. (2012) focus in their study on the comparison between the NSM and the SVM for the estimation of the yield curve on the Croatian financial market. They find out that the Svensson model is superior to the Nelson-Siegel model. Moreover, Ioannides (2003) uses different spline-based models, the NSM and the SVM in order to estimate the yield curve in the UK. By estimating the yield curve with different methods, he shows, that the SVM and the NSM outperform the other used spline-based methods. By comparing the SVM with the NSM model, he points out that the SVM is more suitable than the NSM for the yield curve estimation in the UK.

To the best of our knowledge, no study or analysis has focused on the comparison of different nonlinear models and methods for the estimation of yield curve for an interbank credit market, neither on an intraday day basis, nor for higher maturities.

Due to the importance and empirical validity of the previously described three models, the goal of the paper is manifold: first, we aim to find out, whether the NSM, the SVM and the DLM are able to model the SIYC. The second purpose is to discover which model is the most suitable for estimating the SIYC. Using a sample from October 2005 to March 2010 we also put focus on the different states of the interbank credit markets by dividing our sample into different sub-

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[23] The DLM has been also extended/ or modified. Laurini and Hotta (2010) extend the model through a Bayesian estimation method using the Markov Chain Monte Carlo Simulation. Bernadell et al. (2005) present a regime-switching extension of the DLM by linking expectations of different macroeconomic variables to the estimated yield curve.

periods according to different relevant events during the financial crisis starting in 2007. Hence, the importance and the consequences of the financial crisis are explicitly considered. Following e.g. Angelini (2000), Baglioni and Monticini (2008) and Baglioni and Monticini (2010), who use one-hour intervals for the estimation of an intraday term structure on e-MID by applying the linear regression with hourly dummies, we also construct the SIYC over intraday time intervals. However, we do not use one-hour intervals but 30-minute intervals, meaning 30-minute averages for the interest rates. [24]

The paper is organized as follows: After the introduction, we present in section two our data sample and the main descriptive statistics. Section three describes the applied models. In section four we present the empirical results. Here, we first examine whether each model is capable of modeling the SIYC and in the second part we perform the model comparison. In the last part of the section we discuss our empirical results. In the last part of the section we discuss our empirical results. Here we highlight also the practical importance of our empirical findings. Section five concludes.

2.2 e-MID and descriptive statistics

The trading activity on the market begins each day at 08:00 a.m. and ends at 06:00 p.m. During this time credits with a minimum credit value of 50,000 euro can be traded. The maturity of credits ranges from overnight credits (ON) up to one year.[25]

During the transaction process the duration, the interest rate, the specific time and the amount of each credit are known. Furthermore, also the Quoter (bank which puts the order for the transaction in the limit order book) and the Aggressor bank (bank which selects and accepts the specific credit transaction) are known due to a specific code which consists of two letters, referring to the country of origin and four digits which refer to the specific bank.

The exact time of repayment may not be known exactly, but the maximum maturity of the ON credits is predefined by the system itself. If an Italian bank is involved in the credit transaction, either as a Quoter or as an Aggressor, the latest repayment time point of the ON credit is at

[24] The use of different intervals instead of tick-by-tick data is used in different studies focusing on limit order books see e.g. Kempf and Mayston (2005) and Hautsch and Jeleskovic (2008) for financial markets. Moreover, Engler and Jeleskovic (2016) apply the Multivariate Multiplicative Error Model to analyze the order book data on e-MID using 5-minute intervals.

[25] The ON segment represents more than 90% of the credit transactions in terms of volume and number of trades.

09:00 a.m. the next business day. If no Italian bank is involved the latest repayment time is at 12:00 (noon) the next business day.

For our analysis we use a data sample starting on 03.10.2005 up to 31.03.2010. This is a large sample and includes times before, during and after the financial crisis of 2007 and contains 377,745 overnight transactions.

As pointed out in many studies (see e.g. Baglioni and Monticini, 2008 and Baglioni and Monticini, 2010) in the time band between 08:00 a.m. and 09:00 a.m., the trading activity in the e-MID market is very low in terms of volume and number of transactions. Thus, it can be characterized as not sufficient in this particular daily time period. This fact can also be observed in our data sample. Only 5,829 overnight transactions occur during the time between 08:00 a.m. and 09:00 a.m., which are approximately five transactions per day, in the whole sample period.

Furthermore, as stated by Gürkaynak et al. (2007) the estimation of the yield curve behaves oddly based on securities with a very short maturity. According to their analysis this fact can be observed due to the relative low liquidity of securities with low maturity. As pointed out by Angelini (2000) this fact can also be observed in the e-MID. We can observe this trend also in our whole data sample. During the time band between 05:00 p.m. and 06:00 p.m., only 5,975 transactions occur during the whole sample period, meaning that only approximately five overnight transactions per day take place in the market during this daily time period.

By considering these two facts, meaning a small number of transactions and low volume between the time bands 08:00 a.m. and 09:00 a.m. and 05:00 p.m. and 06:00 p.m. we focus our estimations for the SIYC during the time between 09:00 a.m. and 05:00 p.m., which is in line with the previous studies as mentioned above. Thus, in our analysis 365,941 out of 377,745 overnight transactions in the sample period are considered, stating for 96.88 % of all the overnight transactions in the sample period in the e-MID.

Out of these overnight transactions, in 345,105 transactions at least one Italian bank was involved, either as a credit lender or as a borrower within the transaction. This represents 94.31% of all ON transactions. In the remaining 20,836 overnight transactions no Italian bank was involved. These credits were completed between foreign banks, accounting for 5.69 % of all ON transactions.

Following different studies, (e.g. Gabbi et al., 2012 and Demertzidis and Jeleskovic, 2016) we separate our data sample into four periods. This is done, due to the fact, that our interest goes further than the simple analysis of the suitability of the different models. We are interested in finding out whether the models are capable of estimating the SIYC in different sub-periods and which model performs the best in the in different periods, and different states of the market, before, during and after the financial crisis. Hence, splitting up our sample in this way enables this kind of analysis.

The first period, which we call the pre-crisis period, starts on 03.10.2005 until 08.08.2007 - one day before the onset of the global financial crisis. The second period ranges from 09.08.2007, the onset of the crisis, up to the 14.09.2008, one day before the collapse of the bank Lehman Brothers. Hence, we define it as the first crisis period. The third period ranges from 15.09.2008 until 12.05.2009, one day before the last reduction of the key interest rate by the European Central Bank (ECB). We call this period the second period of the crisis. The last period ranges from 13.05.2009 until the end of the sample on the 31.03.2010. This period can be called the after-crisis period.[26] The different periods for our estimations are summarized in table 2.1.

Table 2.1: Presentation of the sub-periods

Period 1	03.10.2005-08.08.2007	Period before the crisis
Period 2	09.08.2007-14.09.2008	Outbreak of the crisis until the collapse of Lehman Brothers
Period 3	15.09.2008-12.05.2009	Lehman Brothers collapse until reduction of key interest rate
Period 4	13.05.2009- 31.03.2010	Key interest rate reduction until the end of the observation period

The main descriptive statistics for the credit transactions considered in our data sample are summarized in the tables 2.2- 2.5.

[26] Brunetti et al. (2019) refer to the period from April 2009 to March 2010 as the after-crisis period.

Table 2.2: Descriptive statistics: days and observations [27]

	Whole Sample	Period 1	Period 2	Period 3	Period 4
Number of days	1,641 (1149)	675 (473)	403 (281)	240 (166)	323 (229)
Transactions	365,941	182,876	97,281	41,858	43,926
Mean of transactions per day	318.49	386.63	346.19	252.16	191.82

Based on table 2.2 we can see that, the mean number of transactions in the whole sample is 318.49 trades per day. What is more interesting is that the number of trades is the highest before the crisis (period 1) and starts do drop slowly with the onset of the financial crisis in the second period. This trend becomes even more acute in period 3, the second crisis period, where the mean number of transactions drops dramatically, resulting in an even sharper drop in the number of transactions in period 4 in our data sample.

The descriptive statistics regarding the volume of transactions can be found in table 2.3.

Table 2.3: Descriptive statistics: volume (in Million Euros)

	Whole Sample	Period 1	Period 2	Period 3	Period 4
Daily average	13,116.69	19,779.45	13,000.34	6,977.88	3,947.49
Mean per Transaction	41.18	51.16	37.55	27.67	20.58

Regarding the descriptive statistics in terms of volume, we can state that, the trading volume, as daily average volume and mean per transaction, follow the same trend as the number of

[27] In parentheses: effective trading days, excluding weekends and holidays.

trades in table 2.2. We see that the volume is the highest before the crisis, drops in periods 2 and more in period 3. The lowest volume per day and per transaction is found in period 4.

Table 2.4: Descriptive statistics: interest rates

	Whole Sample	Period 1	Period 2	Period 3	Period 4
Mean	2.605	3.050	4.036	2.029	0.355
Std. Dev.	0.032	0.014	0.0389	0.081	0.027

Considering the descriptive statistics of the interest rate, which are calculated over half hour time intervals, we can see that the mean of the interest rate is quite high in period 1 and the highest in period 2. After the culmination of the financial crisis the interest rate dropped in period 3 and even more in period 4. Regarding the standard deviation, one can see that the smallest grade of variation of the interest rates is observed in the first period in our data sample whereas the highest one is in the second period. After the second period the standard deviation is successively declining in the periods 3 and 4. These results for the standard deviation rely on the fact that before the outbreak of the financial crisis the dynamic of interest rates is quite flat.[28] On the other hand, this implicates that the strongest variation in the dynamic of interest rates can be assumed in the period 2.

As already discussed by Demertzidis and Jeleskovic (2016) the market functions properly before the crisis and in the first period of the crisis. They further state that the market does not function properly in periods 3 and 4, meaning that the effective allocation of credits is no longer possible. This effect is also supported in our data sample in terms of volume and number of trades.

2.3 Methodology of the SIYC estimation

As already mentioned above and in contrast to previous studies, we use 30- minute intervals for the estimations of the SIYC-s. There are at least two reasons to use half hour intraday intervals. First, the construction of the SIYC becomes more precise, and thus, the estimation of the SIYC as well. Second, from the practical point of view the traders on the e-MID may be more interested in the nowcasting of the interest rate in shorter time intervals due to the fact that they trade

[28] This fact was also observed by Baglioni and Monticini (2013).

more frequently within the intraday time domain. Hence, in our opinion the use of half-hour intervals is an appropriate solution for the tradeoff between avoiding the noise in the tick-by-tick data and the practical advantage of not-using intervals which are too long.

Therefore, in our data sample we use 16 mean interest rates per day, meaning 16 intervals, starting from 09:00 a.m. - 09:30 a.m. which represents the first interval at the time stamp 09:30 a.m., until the time band from 04:30 p.m.- 05:00 p.m. which represents the last intraday interval for 05:00 p.m.

To estimate the empirical SIYC, it is necessary to define the maturity of each credit transaction in our data sample. We calculate the maturity of each credit interval as the difference between the time stamp of the particular half hour interval within a day and 06:00 p.m., when the market closes on each day. Thus, because we use the pre-described time bands between 09:30 a.m.- 05:00 p.m. , the maximum maturity is 8.5 hours (09:30 a.m.- 06:00 p.m.) and the minimum maturity is one hour (05:00 p.m.- 06:00 p.m.).[29]

We can state that these time intervals of 30 minutes generate a high number of observations needed for the empirical analysis of the SIYC on the e-MID market. We point out that we also estimated the yield curve using time intervals of one, five and fifteen minutes and within the interval of one hour. However, the results do not differ qualitatively and are even slightly worse in terms of quantitative results.[30]

2.3.1 The Nelson- Siegel Model

Nelson and Siegel (1987) propose the following equation for the estimation of the spot rate R of different maturities (m):

$$R(m) = \beta_0 + \beta_1 \frac{1-e^{\frac{-m}{\tau}}}{\frac{m}{\tau}} + \beta_2 \left(\frac{1-e^{\frac{-m}{\tau}}}{\frac{m}{\tau}} - e^{\frac{-m}{\tau}} \right) \qquad (2.1)$$

Where β_0, β_1, β_2 specify the parameters to be estimated and τ denotes the time constant associated with the equation.

[29] The first interval lies between 09:00 a.m. and 09:30 a.m.

[30] The problem occurs by the use of shorter time intervals that in a certain number of intervals there are no credit transactions. This may cause some artifacts and impact negatively the numerical optimization. However, these results can be provided on request.

β_0, is a constant. For a maturity which is approaching infinity, the spot rates converge to this value. The second term $\beta_1 \frac{1-e^{\frac{-m}{\tau}}}{\frac{m}{\tau}}$, refers to the slope of the specific yield curve and the third term of the model $\beta_2 \left(\frac{1-e^{\frac{-m}{\tau}}}{\frac{m}{\tau}} - e^{\frac{-m}{\tau}} \right)$, is important for the modeling of a hump or a U- shape in the yield curve. In our case R is the mean of interest rates within a half hour interval and m is the maturity defined as above.

The estimation of the NSM relies on the same procedure as in Demertzidis and Jeleskovic (2016). We estimate each parameter of the NSM by fitting R(m) based on formula (2.1). During this process we apply a numerical optimization where we apply an objective function over τ, whereas each parameter is estimated simultaneously in each optimization step using the ordinary least squares (OLS) method. During our analysis we use the fminbnd function for our optimization process, with default settings. The optimization bounds for τ lie between 0 and 10000 during our estimations.

2.3.2 The Svensson Model

In order to increase the goodness-of-fit and the flexibility of the yield curve Svensson (1994) extended the NSM by adding a fourth term. By adding this fourth term, it is possible to model a second hump, or a second U- Shape, in the yield curve (Svensson 1994). He validates his findings by estimating the yield curve of Swedish government bonds in the time between May 1992 and June 1994.

For the estimation of the spot rate R, with a yield to maturity denoted m, Svensson uses the equation:

$$R(m) = \beta_0 + \beta_1 \frac{1-e^{\frac{-m}{\tau_1}}}{\frac{m}{\tau_1}} + \beta_2 \left(\frac{1-e^{\frac{-m}{\tau_1}}}{\frac{m}{\tau_1}} - e^{\frac{-m}{\tau_1}} \right) + \beta_3 \left(\frac{1-e^{\frac{-m}{\tau_2}}}{\frac{m}{\tau_2}} - e^{\frac{-m}{\tau_2}} \right) \tag{2.2}$$

Where b is: β_0, β_1, β_2, β_3 are the parameters of the estimated yield curves and the parameters τ_1 and τ_2 are the time constants of the model.

In this equation the term $\beta_3 \left(\frac{1-e^{\frac{-m}{\tau_2}}}{\frac{m}{\tau_2}} - e^{\frac{-m}{\tau_2}} \right)$ defines the second hump, or the second U shape in the yield curve and the parameter τ_2 the position of this positive or negative hump. All the other parameters, including their asymptotic properties, can be defined like the model proposed by Nelson and Siegel (Svensson, 1994).

In his model, Svensson uses the Maximum likelihood method in order to estimate the parameters. According to Svensson the estimated prices can be fitted to the actual (observed) prices also with the general method of movements and the nonlinear least squares method (Svensson, 1994).

In our case, we use the nonlinear least squares method where we apply the Matlab algorithms and the optimization toolbox. However, as Gilli et al. (2010) report there may be a significant problem with the objective function when optimizing the Svensson model. As the authors report, the optimization problem might be non-convex and there may be different local minima. To avoid these problems, we use at first the genetic algorithm. Having optimized the parameters in the Svensson model via the genetic algorithm, we take the optimal parameters to use them as starting values for the numerical optimization in the second step. We are convinced that this procedure will lessen the problem of starting values and local minima.

2.3.3 The Diebold- Li Model

Diebold and Li (2006) modified the original NSM and use at first a two-step estimation method for the parameter estimation. In their work they fitted the yield curve using a three-factor model based on the NSM. Equation 2.3 presents the three-factor model from Diebold and Li (2006).

$$y(\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau}\right) + \beta_{3t}\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau} - e^{-\lambda_t\tau}\right) \tag{2.3}$$

Diebold and Li interpret the parameters β_{1t}, β_{2t} and β_{3t} as latent dynamic factors which vary over time and thus, they are state-dependent. The loading on β_{1t} equals one, which can be viewed as the long-term factor. The term $\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau}$ is the loading of the parameter β_{2t}, which starts at the value of one and guarantees a quick and monotonical decay towards 0. So, it can be interpreted as the short-term factor. The factor loading of β_{3t}, is $\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau} - e^{-\lambda_t\tau}$. The value starts at 0, increases in the beginning and then decays to zero, so it can be viewed as the medium-term factor (Diebold and Li, 2006).

Another important insight of this extension is that the parameters β_1, β_2 and β_3 can be interpreted in another way than in the original NSM. Diebold and Li interpret these parameters as the level, slope and curvature of the yield curve respectively (Diebold and Li, 2006).

The last parameter λ, which is $1/\tau$ in the original NSM, explains the exponential decay rate. When λ takes small values, it results in a slow decay, so the model can fit the yield curve better at long maturities. If λ takes large values the decay is faster, resulting in a better fit at short maturities. Besides the decay rate the parameter λ defines where the loading of β_3 achieves his maximum. In their work this parameter stays constant at the value of 0,.609 for every given t (Diebold and Li, 2006).

We do the estimation process based on Diebold et al. (2006),using the Kalman filter method for the yield curve, due to the fact, that we obtain better results with this method than with the original proposed two step method for the estimation.[31]

For the estimation of the SIYC using the DLM we use the SSM econometrics toolbox in Matlab. Here for the state vector x_t and the observation vector y_t the parametric form us given by the following linear state- space functions:

$$x_t = A_t x_{t-1} + B_t u_t \qquad (2.4)$$

$$y_t = C_t x_t + D_t \varepsilon_t \qquad (2.5)$$

Here, u_t and ε_t are unit-variance white noise vector processes which are uncorrelated. In this representation the first equation is called the state equation and the second one is the observation equation. The parameters of the model, A_t, B_t, C_t and D_t are referred to as the state transition, state disturbance loading, measure sensitivity and observation innovation matrices, respectively.

The DLM is formulated in such a way that level, slope and curvature follow a VAR (1) or autoregressive process of first order and as such the model forms a state space system. As already mentioned, we use the interpretation of Diebold et al. (2006) statingtransition equation, which govern the dynamics of the state vector and it is written as:

$$\begin{pmatrix} L_t - \mu_L \\ S_t - \mu_s \\ C_t - \mu_c \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{11} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} L_{t-1} - \mu_L \\ S_{t-1} - \mu_S \\ C_{t-1} - \mu_C \end{pmatrix} + \begin{pmatrix} \eta_t(L) \\ \eta_t(S) \\ \eta_t(C) \end{pmatrix} \qquad (2.6)$$

Whereas the corresponding observation equation is written as:

$$\begin{pmatrix} y_t(\tau_1) \\ y_t(\tau_1) \\ \vdots \\ y_t(\tau_N) \end{pmatrix} = \begin{pmatrix} 1 & \frac{1-e^{-\lambda\tau_1}}{\lambda\tau_1} & \frac{1-e^{-\lambda\tau_1}}{\lambda\tau_1} - e^{-\lambda\tau_1} \\ 1 & \frac{1-e^{-\lambda\tau_2}}{\lambda\tau_2} & \frac{1-e^{-\lambda\tau_2}}{\lambda\tau_2} - e^{-\lambda\tau_2} \\ & \vdots & \\ 1 & \frac{1-e^{-\lambda\tau_N}}{\lambda\tau_N} & \frac{1-e^{-\lambda\tau_N}}{\lambda\tau_N} - e^{-\lambda\tau_N} \end{pmatrix} \begin{pmatrix} L_t \\ S_t \\ C_t \end{pmatrix} + \begin{pmatrix} e_t(\tau_1) \\ e_t(\tau_2) \\ \vdots \\ e_t(\tau_N) \end{pmatrix} \qquad (2.7)$$

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[31] The results of the SIYC estimation of the DLM using the two-step method can be submitted upon request.

In the vector notation the DLM can be rewritten as the following state space system for the 3-D vector of mean-adjusted factors f_t and the observed yields y_t:

$$(f_t - \mu) = A(f_{t-1} - \mu) + \eta_t \qquad (2.8)$$

$$y_t = \Lambda f_t + e_t \qquad (2.9)$$

With the orthogonal, Gaussian white noise processes η_t and e_t are defined as following:

$$\begin{pmatrix} \eta_t \\ e_t \end{pmatrix} \sim WN\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} Q & 0 \\ 0 & H \end{pmatrix}\right) \qquad (2.10)$$

In this setting, it is assumed that the stochastic terms for the state factor disturbances η_t are correlated leading to a non-diagonal covariance matrix Q which is non-diagonal. On the other hand, the diagonality of the covariance matrix H is assumed so that the deviations of the observed yields among all maturities are uncorrelated.

The latent states are to be defined as the mean-adjusted factors:

$$x_t = f_t - \mu \qquad (2.11)$$

And the deflated or, intercept-adjusted yields as:

$$y'_t = y_t - \Lambda_\mu \qquad (2.12)$$

And then substitute into the equations above.

Thus, the DLM state-space system may be rewritten as:

$$x_t = Ax_{t-1} + \eta_t \qquad (2.13)$$

$$y_{t'} = y_t - \Lambda_\mu = \Lambda x_t + e_t \qquad (2.14)$$

$$\eta_t = Bu_t \qquad (2.15)$$

$$e_t = D\varepsilon_t \qquad (2.16)$$

$$Q = BB' \qquad (2.17)$$

$$H = DD' \qquad (2.18)$$

As already mentioned, the yields-only model forms a state-space system, with a VAR(1) transition equation where the dynamics of the vector of latent state vector variables are summarized, and a linear measurement equation relating to the observable yields to the state vector. For the estimation purposes, we use the SSM toolbox using the smoother algorithms and the default specifications given by this toolbox. Due to the often referred to problem of the sensitivity of

Kalman filter estimator on starting values, we span a grid of starting value for parameter λ in the range between 0.00001 and 0.5 and took the best estimates.

2.4 Results

In order to verify, whether these models are suitable for estimating the SIYC and to compare their empirical performance in each sub-period, we evaluate the models using three different measures, namely the standard R^2 since it also has been used by Nelson and Siegel (1984), the Root Mean Squared error (RMSE), which has been used by Svensson (1994) to evaluate his model and the Mean Absolut Error (MAE).[32]

An important fact of the RMSE is that it is based on the squared errors and thus sensitive to outlier in the error distribution. Hence, relatively higher weights are put on the tails of the error distribution using RMSE as a measure of goodness-of-fit. In an analogous way, this holds true also for R^2.[33] On the other hand, the Mean Absolute Error (MAE) may be quite robust to the outliers, and thus, has some advantages compared to the other two. Therefore, we can consider the MAE as a robust measure of the goodness-of-fit. Hence the both measures of the goodness-of-fit, namely the MAE and the RMSE, may behave differently when one uses them for the purposes of the measures of the model fit. Relying on this fact, we will use all three measures when we are analyzing the three models applied in this paper.

In the first part of this chapter, we evaluate each model separately by the three measures over the four periods to identify if there are significant changes. In the second part, we compare the three models with each other over periods, again based on those three measures, and in the third part we discuss our findings.

2.4.1 Empirical results for the comparison between the periods

2.4.1.1 Evaluation based on the R^2

We calculate the R^2 for each day using the following formula:

$$R^2 = 1 - \frac{\sum(r_i - \hat{r}_i)^2}{\sum(r_i - \bar{r}_i)^2} \qquad (2.19)$$

[32] As already mentioned we focus on the comparison based on in-sample statistics. This is the reason why we use these kind of measurements and not others e.g. the Diebold Mariano test (Diebold and Mariano, 2002), which is mainly used in out of sample comparisons (Clarida et al., 2003).

[33] However, the R^2 takes additionally the variation of the dependent variable into account.

where r_i stands for the mean interest rate of the i_{th} 30- minute interval within a day, $\hat{r}_i$ stands for its estimated interest rate and $\bar{r}_i$ stands for the mean of all 16 r_i-s on the particular estimation day. Thus, we have as many estimates of R^2-s as the number of days we consider in a sample. After that, we can analyze the statistical properties of calculated R^2-s. In the same way, we proceed with other two measures of fit.

Table 2.5 presents the results for the R^2 in the different periods for the estimations of the intra-day yield curve in the e-MID market using the NSM.

Table 2.5: R^2 of the NSM

	Period 1	**Period 2**	**Period 3**	**Period 4**
R^2	0.6732***	0.7398***	0.6612***	0.6259***
Std. Dev.	0.2190	0.2023	0.1977	0.2050
t-statistic	66.847	61.294	49.092	46.201

*** Denotes significance on the 1% level

Hence, these results present the mean and the standard deviations of the R^2-s, and the t-statistics for the means in each period, respectively. First given the high mean of R^2 in each period, we can state that the NSM is capable of modelling the SIYC in the e-MID market. Second, we can also state that, the best performance for the modeling of the SIYC can be found in period 2 with an R^2 of 0.7398, thus, this is in the offset of financial crisis. This is a first support of results given by Demertzidis and Jeleskovic (2016) that the best performance of the NSM may be achieved in period 2. Although distortion on the interbank credit markets where noticeable, the market was still functioning properly, as already mentioned above. The second-best performance is found in period 1 which is the pre-crisis period where an R^2 of 0.6732 is achieved. The performance drops slightly in period 3, where we achieve a mean R^2 of 0.6612 which is quite similar to the period 1. Furthermore, the smallest mean R^2 of 0.6259 is achieved in period 4. Although the achieved means of R^2 are remarkably high, we use the standard t-test in order to find out whether these means are significantly different from zero using the following formula:[34]

$$t = \sqrt{n}\frac{\bar{x} - \mu_o}{s} \qquad (2.20)$$

[34] We use this test also for the analysis of the MAE and the RMSE.

where *n* stands for the number of observations, $\bar{x}$ stands for the mean of the respective goodness-of-fit statistic, in this particular case of R^2, *s* stands for the standard deviation of that specific goodness-of-fit statistic, and μ_o is zero, since we test against zero.

Based on the t-test we can state, that the R^2 are significantly different from zero even at the 1% level in each sub- period.

To find out whether the means of the considered statistics for goodness-of-fit from the different periods of the same model[35] are significantly different, we use the two-sample two-tailed t-test between the periods:

$$t = \sqrt{\frac{nm}{n+m}} \frac{\overline{x_1} - \overline{x_2}}{s} \qquad (2.21)$$

$$s^2 = \frac{(n-1)^2 s_1^2 + (m-1)^2 s_2^2}{n+m-2} \qquad (2.22)$$

where *n* and *m* stand for the number of observations of the same statistics from two periods, respectively, which we want to compare statistically with each other. The two statistics are in our case the means of the particular measure of fit, here $\overline{x_1}$ and $\overline{x_2}$, and can stem from two different periods for the same model. s_1^2 and s_2^2 are the estimated variances of $\overline{x_1}$ and $\overline{x_2}$. The results of the two-sample t-test between each period for the NSM are presented in table 2.6.

Table 2.6: Two-sample t-test of R^2 for the SIYC-s estimated by the NSM

	Period 2	**Period 3**	**Period 4**
Period 1	-4.151***	0.622	2.736***
Period 2		4.001***	6.283***
Period 3			1.714*

***, **, * Denote significant different means at the 1%, 5% and 10% level respectively.

The difference between period 2 and all other periods is significant even at the 1% level. Hence the NSM achieves significantly the best performance in period 2. In addition, the difference between period 1 and period 4 is highly significant, whereas the difference between period 1 and period 3 is statistically not significant. Between period 3 and 4 we can state significantly different means of R^2 only at the 10 % level. These results for the NSM are in line with the

[35] Or of two models from the same period.

results provided by Demertzidis and Jeleskovic (2016). Therefore, the same economic discussion given by Demertzidis and Jeleskovic (2016) regarding their results for the NSM also holds in the case of results in this paper for the NSM when comparing different periods. Thus, the main conclusion is that the best performance of NSM is achieved in the period of the onset of the financial crises with a proper functioning interbank credit market.[36]

The means of R^2 for the SVM for the different sub-periods are presented in table 2.7.

Table 2.7: R^2 of the SVM

	Period 1	**Period 2**	**Period 3**	**Period 4**
$\boldsymbol{R^2}$	0.7863***	0.8243***	0.7517***	0.7176***
Std. Dev	0.1740	0.1682	0.1723	0.1892
t-statistic	97.566	82.121	56.202	57.400

*** Denotes significance on the 1% level

Based on the means of R^2 we can state that the SVM is also suitable for an empirical estimation of the SIYC in the e-MID market. These means of R^2 follow the same tendency as in the previously presented results for R^2 of the NSM. The best performance of the SVM can be found in period 2, with a mean R^2 of 0.8243. The second best can be found in period 1 of 0.7863 whereas in period 3 the mean drops to 0.7517 and even more in period 4 where we achieve a mean R^2 of 0.7176. Moreover, these means are significantly different from zero at the 1% level as well, as the t-test indicates.

Regarding the significance among the different periods, we can state that the results of the two-sample t-test of the SVM, presented in table 2.8, are also qualitatively the same as in the case of the NSM. The only difference here is that the difference between the mean of period 1 and period 3, is significant at the 10 % level. This fact does not change qualitatively the implication of the results which can be taken over as for the NSM.

[36] For further information, see Demertzidis and Jeleskovic (2016). This conclusion holds also for the SVM and the DLM, as will be presented below.

Table 2.8: Two-sample t-test of R^2 for the SIYC-s estimated by the SVM

	Period 2	Period 3	Period 4
Period 1	-3.375***	1.847*	4.367***
Period 2		4.369***	6.732***
Period 3			1.832*

***, **, * Denote significant different means at the 1%, 5% and 10% level respectively.

The mean of R^2 for the DLM for the different periods can be found in table 2.9 where additionally the estimated mean of the $\boldsymbol{\lambda}$ parameter is presented.

Table 2.9: R^2 of the DLM

	Period 1	Period 2	Period 3	Period 4
$\boldsymbol{R^2}$	0.6025***	0.6823***	0.6444***	0.6020***
Std. Dev	0.2491	0.2353	0.2057	0.2224
t-statistic	52.589	48.605	40.364	40.964
$\bar{\boldsymbol{\lambda}}$	0.0007	0.1681	0.0407	0.0400

*** Denotes significance on the 1% level

First, we can state that also the DLM, like the NSM and the SVM, is capable of estimating the SIYC for the e-MID market. Also, like the NSM and the SVM the best performance can be found in period 2 where we achieve a mean of R^2 of 0.6823. In contrast to the previous models, the second-best performance cannot be found in period 1 but in period 3 with an R^2 of 0.6444. Furthermore, the results of the periods 1 and 4 are quite similar and lower than in the previously described periods, where we achieve an R^2 of 0.6025 and 0.6020 respectively. Like the previous two models, the R^2 of the DLM in each sub-period are statistically different from zero at the 1% level. Hence, the DLM is suitable for the modeling of the SIYC as well. These similarities in the findings are also supported by the two-sample t-test for the DLM presented in table 2.10.

Table 2.10: Two-sample t-test of R^2 for the SIYC-s estimated by the DLM

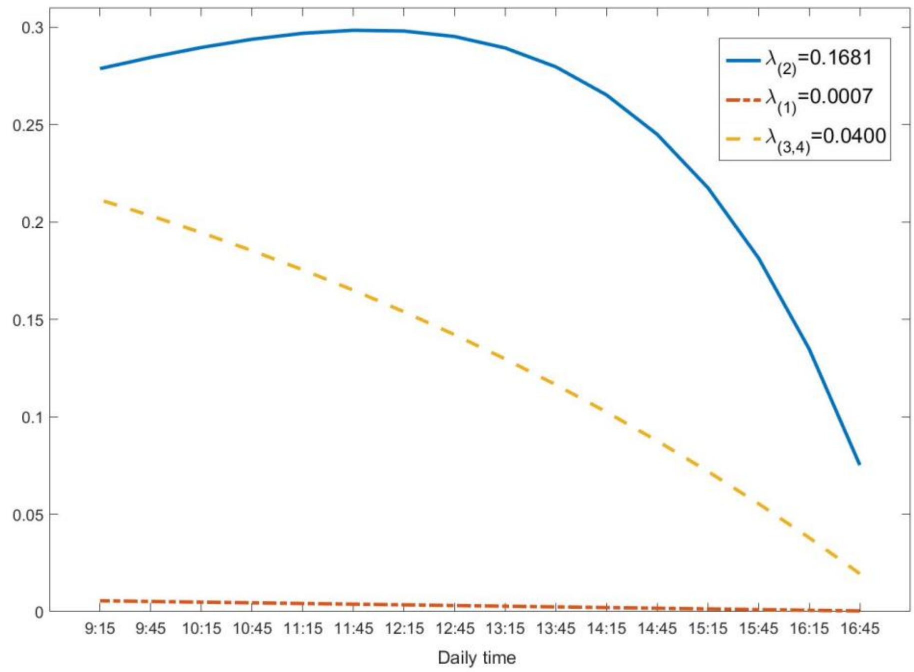
	Period 2	**Period 3**	**Period 4**
Period 1	4.344***	-1.947*	0.21
Period 2		1.724*	3.927***
Period 3			1.927*

***, **, *Denotes significant different means at the 1%, 5% and 10 % level respectively.

Based on this test, we can state that the differences between period 1 and 2 and for the periods 2 and 4 are significant also at the 1% level. The differences between period 1 and 3, period 2 and 3 and period 3 and 4 are significant at the 10% level whereas the difference between period 1 and 4 are not significant even at the 10% level. Thus, the best model performance can also be found here in period 2 and the worst one in period 4. Furthermore, the most important economic discussion regarding the goodness-of-fit in period 2 given by Demertzidis and Jeleskovic (2016) holds also for DLM. The only difference to the qualitative results achieved through NSM and SVM lies in the comparison between the periods 1 and 3 where, however, this difference between these two periods is significant only on the 10% level. Hence, we deem this evidence to be a matter for our future interest.

At this point, we tackle the same discussion about the curvature as in Diebold and Li (2006) which correspond to the following figure 2.1.

Figure 2.1: Curvature regarding estimated $\lambda_{(1)}$,$\lambda_{(2)}$, $\lambda_{(3)}$, and $\lambda_{(4)}$ for the periods 1, 2, 3, and 4, respectively.



As it can be seen in figure 2.1, the middle of each half hour interval is used to construct this graph which is correct when we assume the uniform distribution within the intervals. Due to the very small differences between estimated $\boldsymbol{\lambda}_{(3)}$ and $\boldsymbol{\lambda}_{(4)}$, and thus both corresponding curves cannot be graphically distinguished, we present only one curve for both periods which corresponds to $\boldsymbol{\lambda}_{(3,4)}$. Note that in our case the first intraday interval from 9:00 a.m. to 9:30 p.m. has the longest maturity and the last one from 04:30 p.m. to 05:00 p.m. has the shortest maturity. Hence, these functions are turned around compared with the curvature presented by Diebold and Li (2006).

We can recognize that the loadings on the curvature in period 1 is very small and quite flat whereas it has a negative slope and is monotonically decreasing. It is monotonically decreasing in periods 3 and 4 as well. However, the difference here is that these loadings are remarkably high, and the nonlinearity is to some extent obvious. So, all three loadings in periods 1, 3, and 4 support the hypotheses of monotonically decreasing interest rates during a day advocated by e.g. Baglioni and Monticini (2008) and explained by the intraday risk premium. However, the interesting result can be seen in period 2. A curvature with the maximum peak around noon is estimated. This is clear evidence of a highly nonlinear shape due to the curvature factor within the SIYC in period 2.

Furthermore, regarding our findings from the tables 2.5, 2.7 and 2.9 we can state that, based on the R^2 all three models are capable of modelling the SIYC in the e-MID market. To the best of our knowledge, such high R^2 have not been achieved in similar studies by analyzing the intraday interest rates on an interbank credit market.

In his empirical study, Angelini (2000) states that quite low R^2 of 0.02 for the modeling of the intraday term structure can be achieved, accenting this weak evidence for an intraday downtrend. As he uses a “pre-crisis period” we can state that the standard nonlinear models for the estimation of the SIYC surpasses linear models like of Angelini (2000).

Our results further indicate that our empirical findings are better than those obtained by Baglioni and Monticini (2008) where their model achieves an R^2 of 0.09 and who also estimate there the term structure in a pre-crisis period.

Baglioni and Monticini (2010) state that they achieve an R^2 of 0.34 before the outbreak of the crisis on 9th August 2007 and of 0.21 after that. Hence, from their point of view, there may be a higher difference between the morning and afternoon interest rates but on the other hand, it seems, due to lower R^2 that the assumption of the simple downtrend in the intraday term structure becomes less reasonable after the outbreak of the financial crisis. Moreover, our results indicate that the best goodness-of-fit can be achieved immediately after the outbreak of the financial crisis starting in 2007 using nonlinear models for the estimation of the SIYC.

In terms of goodness-of-fit the closest results to ours are those obtained by Baglioni and Monticini (2013) who are able to achieve estimated R^2 of 0.367, 0.402 and 0.424, using three different linear models. Still, their results are not nearly as good as the ones presented in this paper.

2.4.1.2 Evaluation based on the MAE

We calculate the MAE, analogy to the above analysis of R^2-s, for each day based on the following formula:

$$MAE = \frac{1}{n}\sum_{i=}^{n} |\hat{r}_i - r_i| \qquad (2.23)$$

where $\hat{r}_i$ is the estimate for r_i.

The results for the means of MAE of the NSM are summarized in table 2.11.

Table 2.11: MAE of the NSM

	Period 1	**Period 2**	**Period 3**	**Period 4**
NSM	0.0047	0.0111	0.0313	0.0114
St. Dev.	0.0100	0.0137	0.0177	0.0087

For the NSM we can state, that based on the MAE, the best model performance can be found in period 1 followed by the periods 2, 4 and 3 respectively, whereas the difference between periods 2 and 4 can be considered relatively small. Based on these statistics we can use the two-sample t-test given by formula 2.21 to analyze the performance of the NSM based on the MAE between the different periods.

The results of the two-sample t-test between the periods are summarized in table 2.12.

Table 2.12: Two-sample t-test of MAE for the SIYC-s estimated by the NSM

	Period 2	**Period 3**	**Period 4**
Period 1	-7.380***	-23.507***	-8.609***
Period 2		-13.423***	0.264
Period 3			14.648***

***Denotes significant different means at the 1%.

Regarding table 2.12 we can state, that the MAE between all periods are statistically different at the 1% level, except the difference between period 2 and 4. Hence, the difference in MAE between these two particle periods cannot be considered as significant. This implies that the MAE for the NSM is significantly the best in the period 1, before the crisis. The worst performance can be found in period 3, within the crisis, when the market is not functioning well.

The results of the means of MAE for the SVM are summarized in table 2.13.

Table 2.13: MAE of the SVM

	Period 1	Period 2	Period 3	Period 4
MAE	0.0033	0.0079	0.0253	0.0096
St. Dev.	0.007	0.0097	0.0143	0.0079

Based on table 2.13 we can state that the findings follow the exact same tendency as the NSM. Based on the MAE the best model performance can be found again in period 1, followed by periods 2, 4 and 3, whereas the difference between the periods 2 and 4 seems relatively small.

The two-sample t-test between the sub-periods confirm these findings. The results of the test are summarized in table 2.14.

Table 2.14: Two-sample t-test of MAE for the SIYC-s estimated by the SVM

	Period 2	Period 3	Period 4
Period 1	-7.501***	-25.635***	-10.586***
Period 2		-15.224***	-2.091**
Period 3			13.875***

***, ** Denotes significant different means at the 1% and 5% level respectively.

Based on this test, we can state that all differences are statistically different at the 1% level, except between periods 2 and 4 where we have statistically different means at the 5% level.

The results of the means MAE for the DLM are summarized in table 2.15.

Table 2.15: MAE of the DLM

	Period 1	Period 2	Period 3	Period 4
MAE	0.0054	0.0126	0.0318	0.0117
St. Dev.	0.0112	0.0153	0.0177	0.0091

Based on table 2.15 we can state that the DLM achieves the best performance based on the MAE in period 1 and the worst in period 3, as in the case of the NSM and the SVM. The difference here is, that using this model, the model performance in period 4 is better than in period 2. However, this difference in the performance of the DLM is not statistically different as the two-sample t-test between the periods in table 2.16 indicates.

Table 2.16: Two-sample t-test of MAE for the SIYC-s estimated by the DLM

	Period 2	**Period 3**	**Period 4**
Period 1	-7.382***	-22.204***	-7.449***
Period 2		-12.129***	0.720
Period 3			14.707***

*** Denotes significant different means at the 1% level.

Based on table 2.16 we can state, that the MAE between the periods are statistically different at the 1% level, except between period 2 and 4 where we cannot confirm statistically different MAE-s with NSM and DLM, but at 5% with SVM.

The results based on the MAE are quite different to the results given by the analysis of the R^2 which also shows up regarding RMSE in the next section. We will discuss this fact in section 2.4.3.

2.4.1.3 Evaluation based on the RMSE

In this section we present results for the RMSE. The RMSE can be calculated using the formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{r}_i - r_i)^2} \qquad (2.24)$$

Table 2.17 presents the mean RMSE in the different periods for the estimations of the SIYC in the e-MID market for the NSM.

Table 2.17: RMSE of the NSM

	Period 1	**Period 2**	**Period 3**	**Period 4**
RMSE	0.0060	0.0141	0.0397	0.0148
St. Dev.	0.0131	0.0172	0.0228	0.0122

Based on table 2.17 we can state that best model performance of the NSM can be found in period 1, followed by period 2, period 4 and period 3, respectively.

From the point of view of the statistical inference, these findings are mostly verified by the two-sample t-test between the different periods, which are summarized in table 2.18.

Table 2.18: Two-sample t-test of RMSE for the SIYC-s estimated by the NSM

	Period 2	**Period 3**	**Period 4**
Period 1	-7.261***	-23.032***	-8.456***
Period 2		-13.404***	-0.480
Period 3			14.003***

***Denotes significant different means at the 1%.

Here we can state that the results of the RMSE are statistically different even at the 1% between all periods besides period 2 and 4 where there is no statistically significant difference.

The means of the RMSE for the SVM are presented in table 2.19.

Table 2.19: RMSE of the SVM

	Period 1	**Period 2**	**Period 3**	**Period 4**
MAE	0.0044	0.0103	0.0331	0.0127
St. Dev.	0.0097	0.0126	0.0194	0.0113

Based on table 2.19 we can state that the fit of the SVM for the SIYC-s is best also in period 1 followed by period 2 and period 4 and 3 respectively. Hence these results are qualitatively in line with the results of the NSM.

The results of the two-sample t-test between the periods for the SVM can be found in table 2.20.

Table 2.20: Two-sample t-test of RMSE for the SIYC-s estimated by the SVM

	Period 2	Period 3	Period 4
Period 1	-7.207***	-24.581***	-10.038***
Period 2		-14.995***	-2.200**
Period 3			13.138***

***, ** Denotes significant different means at the 1% and 5% level respectively.

We can see that the results are statistically different at the 1% level among all periods except between the periods 2 and 4 where we can assume the significant differences at the 5% level.

The results of the mean of the RMSE for DLM are summarized in table 2.21.

Table 2.21: RMSE of the DLM

	Period 1	Period 2	Period 3	Period 4
RMSE	0.0076	0.0162	0.0412	0.0156
St. Dev.	0.0168	0.02	0.0236	0.0134

The results of the DLM indicate that the best model performance based on the RMSE can be also found in period 1 and the worst in period 3, as in the case of the NSM and the SVM. However, unlike the other two models the second-best performance is found in period 4. However, the difference between the periods 2 and 4 is not significant, which can be seen in table 2.22 where the results of the two-sample t-test between the periods are presented. In other periods these differences are statistically highly significant.

Table 2.22: Two-sample t-test of RMSE for the SIYC-s estimated by the DLM

	Period 2	Period 3	Period 4
Period 1	-6.301***	-19.729***	-6.224***
Period 2		-11.901***	0.424
Period 3			13.634***

***, ** Denotes significant different means at the 1% and 5% level respectively.

2.4.2 Empirical model comparison

In the previous part of this chapter we stated that all three models are capable of modeling the SIYC. Here we will compare the three different models based on the three measures of model performance with each attempting to answer the question of which model may be the best one for the modeling of the SIYC on the interbank credit market.

2.4.2.1 Model comparison based on the R^2

Based on the tables 2.5, 2.7 and 2.9 we can see that the SVM outperforms the NSM and the DLM in each period. Regarding the comparison between the NSM and DLM we can state that, the NSM surpasses the DLM in each period, however, the results in periods 2 and 3 may not be different to a large extent.

To test if these differences in means are also statistically verified, we perform a two-sample t-test, based on formula 2.21, by testing the means of R^2 between these models. The results of these two-sample tests are summarized in Table 2.23 for each period.

Table 2.23: Two-sample t-test between the models for R^2

	Period 1	**Period 2**	**Period 3**	**Period 4**
NSM/SVM	*-8.351****	*-5.384****	*-4.445****	*-4.975****
SVM/DLM	*12.746****	*8.224****	*5.151****	*5.989****
NSM/DLM	*4.635****	*3.101****	*0.758*	*1.193*

*** Denotes significant different means at the 1% level.

Based on table 2.23. we can state that our previously described findings regarding models' performances and their comparison are also statistically confirmed. The difference in means between the SVM and the NSM and between the SVM and the DLM is significant even at the 1% level. Regarding the comparison between the NSM and the DLM we can state that the differences in periods 1 and 2 are also significant at the 1% level. As already stated in the comparison between the NSM and DLM, the means within period 3 and period 4 do not differ to any great degree from each other. This obviously does not lead to the rejection of the assumption for the equality of those two means.

2.4.2.2 Model comparison based on the MAE

By considering the tables 2.11, 2.13 and 2.15 for the comparison of the models we can state that the SVM dominates the NSM and the DLM in each sub-period as in the case of the R^2. Regarding the comparison between the NSM and the DLM we can state that NSM surpasses the DLM in all sub-periods, though these differences are not as high as in the case of the SVM. To verify statistically our findings based on the MAE we also perform a two-sample t-test between the models. These findings are summarized in table 2.24.

Table 2.24: Two-sample t-test between the models for MAE

	Period 1	**Period 2**	**Period 3**	**Period 4**
NSM/SVM	*2.353***	*3.146****	*3.362****	*2.250***
SVM/DLM	*-3.338****	*-4.273****	*-3.701****	*-2.658****
NSM/DLM	*-1.053*	*-1.197*	*-0.3*	*-0.437*

***, ** Denotes significant different means at the 1% and 5% level respectively.

Based on table 2.24 we can state that the differences regarding the MAE between the NSM and the SVM are statistically different even at the 1% level in the periods 2 and 3, whereas in the period 1 and 4 the differences are significant at the 5% level. Regarding the comparison of the SVM and the DLM we can see that the differences in each period are different at the 1% level. Hence, the dominance of the SVM in comparison to the other two models can be statistically verified. The comparison of the NSM and the DLM shows, that the differences in each sub-period are not statistically different even at the 10%.

2.4.2.3 Model comparison based on the RMSE

Regarding the model comparison based on the RMSE given the results in tables 2.17, 2.19 and 2.21 we can state that the SVM surpasses the NSM and the DLM in terms of a lower RMSE in each period. By comparing the results of the NSM and the DLM we can state that the findings are quite similar, especially in the periods 2,3 and 4. These findings are also confirmed by the two-sample t-test shown in table 2.25.

Table 2.25: Two-sample t-test between the models for RMSE

	Period 1	**Period 2**	**Period 3**	**Period 4**
NSM/SVM	*2.153***	*2.973****	*2.835****	*1.893**
SVM/DLM	*-3.597****	*-4.164****	*-3.392****	*-2.466***
NSM/DLM	*-1.627*	*-1.323*	*-0.574*	*-0.650*

***, **, * Denotes significant different means at the 1%, 5% and 10% level respectively.

By considering these test results we can state that the differences in the RMSE between the SVM and the NSM are highly significant at the 1% in the periods 2 and 3, whereas they are significant at the 5% and 10 % in the periods 1 and 4, respectively. By comparing the SVM and the DLM we can state that the differences in the means of the RMSE are significantly different at the 1% in each period except period 4, where it is significantly different at the 5% level. Regarding the comparison between the NSM and DLM we can state that the differences based on the RMSE are not statistically significant.

2.4.3 Discussion of empirical results

The analysis regarding the goodness-of-fit which is measured by R^2, MAE and RMSE for each model and over different periods reveals some interesting results. At first, all three models provide highly significant goodness-of-fit in each period so that one should consider these models when modeling SIYC on interbank credit markets. By taking a deeper look into the single periods the findings are also quite interesting. Again, these periods are defined as before, directly after the outbreak, during and after the financial crisis of 2007, which means periods 1, 2, 3, and 4 respectively. Having first fitted the SIYC-s to e-MID data and considering the MAE and the RMSE over those sub-periods, the qualitatively same results for NSM and SVM occur. That means that the best performance from both models was achieved in period 1 and the worst one in period 3. Moreover, the performance of these models seems to be better in period 2 than in period 4. The DLM is in line with results from MAE and RMSE for periods 1 and 3 where these results are the best and the worst ones, respectively. However, it is vice versa regarding periods 2 and 4. We point out that the results from the MAE and RMSE for the NSM and DLM between periods 2 and 4 are statistically not different. Hence, we can state that the results from DLM are not in conflict with them from NSM and SVM. Based on the facts that these four periods represent four different states of the market, one can conclude that only the SVM is able to recognize those different market states, and thus, has a further advantage over the NSM and DLM.

Thus, when there is a need to recognize different market states on the interbank credit market, rather the SVM should be applied for these purposes.[37]

The results look differently regarding R^2 when comparing the performance of the models over different sub-periods. Overall, the best goodness-of-fit could be achieved in period 2 and the worst one in period 4 which is in line with results achieved by Demertzidis and Jeleskovic (2016). NSM and SVM have a better performance in period 1 than in period 3 while for DLM it is vice versa. However, using the NSM no significant difference between period 1 and period 3, and using DLM between period 1 and 4 can be found. This is not the case for SVM which detects significant differences among all four periods at least at 10% level of significance. Thus, it implies that the SVM shows again the higher ability, also based on R^2, to distinguish between periods of a properly working interbank credit market and the odd market states. From the economic point of view, this may be an interesting and important finding.

The question arises as to why we get partially inconsistent results when we use MAE and RMSE on the one side and R^2 on the other side. The reason may rely on the variation of the dependent variable in the first period which is small within a day so that daily SIYC-s look quite flat. Whereas MAE and RMSE do not take directly into account the variation of the dependent variable, R^2 does. Given the empirical fact that the variation of interest rates in the first period is very small, compared to other periods before and during the financial crisis, the MAE and RMSE may be *per se* relatively lower in the period 1. On the other hand, the lower variation of the dependent variable has a relevant and direct impact on R^2. This might cause the results that the best fit was achieved in period 1 according MAE and RMSE, and in period 2 according R^2.

After all, one must recognize that when different measures for the goodness-of-fit are used, different qualitative results can be achieved.

Regarding the direct comparison between the three different models, we can state that the SVM dominates the NSM and DLM in each different sub period regarding all three applied statistics. So, SVM may be the advanced model for modeling SIYC on an interbank credit market.

The comparison of results between the NSM and the DLM do not provide overall clear results. Regarding the $R^{2,}$ we can state that the NSM dominates the DLM only in periods 1 and 2, when

[37] However, Demertzidis and Jeleskovic (2016) demonstrate that also the NSM possesses this ability when it is applied to tick-by-tick data on e-MID.

the market is still functioning well, whereas the differences in the means of the R^2 are not statistically significant when the market is not functioning properly in periods 3 and 4. Regarding the comparison of these two models based on the MAE we can state that the differences in the sub periods are not statistically significant. This is also the case when comparing the models based on the RMSE.

Therefore, by taking into account these facts, we can conclude that the statistical justification is given to assume that SVM dominate both other models in terms of the direct comparisons based on different statistics for the goodness-of-fit. Hence, given the fact that SVM is able to model two humps, and thus higher non-linearities, which is, on the other hand, not the case with NSM and DLM we can state that alone the strong nonlinearities in SIYC are ground for such better performance of SVM. However, the NSM and the DLM are able to capture non-linearities in the SIYC as well as what is proven in section 2.4.1. Moreover, in terms of statistical tests, one cannot see the NSM in favor of DLM although the means of three measures of goodness-of-fit are slightly higher for NSM.[38]

As stated by Beaupain and Durré (2013) the interbank credit markets have a major impact for the wellbeing of the financial system as a whole as banks can manage their liquidity needs which again affects the credit conditions for firms and households. Different central banks monitor the well-functioning of the interbank markets as it is of high interest to ensure a smooth transmission of the monetary policy rules to these markets. We demonstrate through the achieved results that these models can support central banks in doing so. Furthermore, they are of high interest for the optimization of the trading strategies of banks as banks can now analyze the intraday dynamics of the interest rate based on results with very high goodness-of-fit of the SIYC. Moreover, the presented results during this study can highlight and improve our understanding of the international interbank credit markets in general.

We achieved empirical results which are superior than in similar empirical studies. This is ensured by our concept of the SIYC which we present. By comparing our findings, with those of other studies in this field, we can state that one must move away from the simple assumption that the intraday interest rate follows a simple linear trend or a monotone function during the day.

[38] Again, the only significant difference in favor of NSM over DLM is given in periods 1 and 2 and based only on R^2.

Additionally, these nonlinear dynamics where highly noticeable especially after the outbreak of the financial crisis in August 2007 which again results in significant better results of our findings. Hence, from a practical point of view, our analysis becomes even more important during these instable times.

2.5 Conclusion

This paper represents the first analysis of the in-sample comparison of three standard models, namely NSM, SVM, and DLM, for the estimation of the non-linear SIYC on the e-MID market and on interbank credits markets on the intraday frequency in general. We apply estimations of the models' parameters based on the half-hourly means of interest rates. Regarding that, this procedure is in line with other comparable studies even though they use hourly intervals of interest rates on e-MID. Moreover, we split the data into four periods before, after the outbreak of financial crisis, after the collapse of Lehman Brothers and after the financial crisis to analyze the effects of the financial crisis of 2007.

We find out that all three models are suitable for the estimation of an intraday yield curve on e-MID. This is based on the fact that the goodness-of-fit of all three models for the SIYC is remarkably high in each period, and thus, these models can be used for the modelling of the SIYC on the e-MID market independently of the state of interbank credit market. For the measure of goodness-of-fit, R^2, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used. Furthermore, compared with the results from other studies, where linear regressions were applied, these three models seem to be highly dominant over all other linear models when comparing the goodness-of-fit measured by R^2. To statistically justify our results and to compare them among different periods, and thus, among different states of interbank credit markets and among these three models, we use corresponding t-tests based on these three measures.

Regarding the analysis among the periods, we find that the highest R^2 can be achieved in period 2 by all three models. The second-best result for R^2 is achieved in period 1 by SVM and NSM. These are periods which are assumed to have a properly functioning market. All three models achieved the smallest R^2 in period 4 when the market liquidity after interventions of ECB was very low. Hence, it is assumed that in this period the market was not functioning properly and due to that, all three models have the smallest R^2. However, also in this odd market state all three analyzed models still achieve remarkably high R^2 which is statistically different from zero by a very high significance level. Using MAE and RMSE, the best goodness-of-fit is achieved in the first period whereas the lowest one is in period 3 by all three models. The reason for this variation in results based on R^2 and other two one measures is that the last two do not directly consider the variation of the dependent variable. Thus, this variation was the lowest one in period 1 so that this fact may cause this discrepancy. Moreover, NSM and SVM achieved second best results regarding MAE and RMSE in period 2 whereas DLM achieves the second-best result in period 4. However, neither NSM nor DLM are able to distinguish a statistically significant difference between period 2 and 4. On the other hand, SVM is able to recognize statistically different results among all four periods using each measure of fit. This is a strong result and we strongly recommend using the SVM when one wants to analyze different market states as in periods before, during and after financial crises.

Furthermore, we find out that, that the SVM, based on the two-sample t-test, dominates the NSM and the DLM regarding in-sample performance measures in all four single periods and regarding all three applied measures. At first sight, the NSM model seems to be the second best model, due to the fact that it dominates the DLM through the different periods and due to the different in-sample statistics. However, these differences in term of goodness-of-fit regarding MAE and RMSE between NSM and DLM are not statistically significant. Hence, one can state in this context that the results from NSM and DLM are not statistically different. Regarding R^2, NSM outperforms the DLM significantly only in periods 1 and 2. Again, these are states when the market was functioning properly.

Hence, our findings state that SVM is to be preferred when an economic analysis on interbank credit market should be conducted. NSM could be preferred over DLM if one conducts the in-sample analysis in interbank credit markets on condition that the market is working properly. However, this finding for NSM and DLM is based only on the goodness-of-fit-measurement given by R^2 and this statement cannot be given based on MAE and RMSE.

These findings again can have a high impact on the optimization of the intraday liquidity management and the trading strategies during the day and are finally of high importance from a policy point of view. Last but not least, our concept of the SIYC for interbank credit markets may attract the application of other models and initialize the out-of-sample analysis which can be also very relevant from the practical point of view.

3. Interbank transactions on the intraday frequency: -Different market states and the effects of the financial crisis-

3.1 Introduction

The beginning of the great financial crisis of 2007 and the events afterwards led us to rethink the architecture of the modern financial system and raised different questions from a practical and theoretical point of view. The major key element of this discussion is the financial interconnectedness that links financial institutions as well as through interbank credit markets (Affinito and Pozzolo, 2017). Due to the well-functioning of the interbank credit markets until that time period the interest on interbank lending was relatively low.

After the outbreak of the financial crisis and the resulting events, the interest in the global interbank credit markets rose again from a theoretical and practical point of view. These markets play a major role in the well-being of the financial system as a whole as banks can manage their liquidity needs. This in turn affects the credit supply of households and firms. Central banks also monitor the well-functioning of the interbank credit markets because it is of great importance to ensure a smooth transmission of the monetary policy rules to this market (Beaupain and Durré, 2013).

One major problem for the analysis of these markets is the data availability. This is the case also for the EONIA (European Overnight Index Average), which represents the only official data for overnight (ON) credits in the Eurozone. Due to the lack of data, it is not possible to audit the market in a more detailed way (Spelta et al., 2019). The data availability of the EONIA, which is only available on the daily frequency, restricts an analysis of intraday patterns on this market (Beaupain and Durré, 2011). Together with the well-functioning of these markets and thus the low research interest, this has been reasons why interbank credit markets and their modeling are still considered by many economists as “black boxes”. Or in other words, as Allen et al. (2019) state, that our knowledge of how the interbank markets work in detail is still very limited. However, a rise in the research interest after the outbreak of the financial crisis in the year 2007 occurred and changed our understanding of it.

The only organized interbank credit market in the Eurozone and the US is the e-MID market (Mercato dei Depositi Interbancario) which is located in Milan, Italy. On this market, banks can allocate liquidity from an ON basis until credits with a maturity of one year. These transactions may be buy-initiated or sell-initiated. The market functions fully transparent and based on the limit order book principle. Beaupain and Durré (2011) show that the e-MID market is a representative market for the whole money market in the Euro area and Arciero et al. (2016) state that this was the fact also until the outbreak of the Italian debt crisis in 2011.[39] Furthermore, this market is taken into account by different policy makers e.g. by the European Central Bank (ECB) (Beaupain and Durré, 2013).

As there is on other interbank credit markets, the ON segment on the e-MID market represents around 90% of the market in terms of the number of transactions and the volume of transactions. As stated in different studies e.g. by Arciero et al. (2016) the e-MID market can be regarded as a benchmark of the Euro area money market, especially on the ON maturity. Again, on the ON basis, the e-MID represented around 53% of the EONIA in terms of volume before the outbreak of the financial crisis in 2007. Especially during the year 2006, it is shown that the market volumes are even higher than the EONIA market (Brossard and Saroyan, 2016).

The e-MID market has undergone systematic changes especially during the financial crisis of 2007, as it was the case for other interbank credit markets (Hatzopoulos et al.,2015). That is the reason why in many different studies, the market conditions are compared, before, during, and after this financial crisis (see e.g. Gabbi et al., 2012, Jeleskovic and Demertzidis, 2018).

A major literature string focuses on the network formations of the e-MID market in the intraday frequency. The analyses from Fricke and Lux (2015), and more recently e.g. Kaltwasser and Spelta (2019) and Spelta et al. (2019), put focus on the network aspects of this e-MID market.

Since the ON segment is the major key element of the market in terms of number and volume of the transactions, different studies focus on the interday and intraday behavior of different interbank variables. On an interday basis, different studies look at interbank variables and their changes among the days. Hartmann et al. (2001) and Beaupain and Durré (2008) analyze the number of trades and the volume of transactions in the interday domain. Gabrieli (2012) analyzes the interday behavior of volumes in the time between 2006 and 2008 and indicates that the volume drops especially after August 2007. Brossard and Saroyan (2016) analyze the shape of the mean daily interest rate in the period between 2006 and 2009. To only name a few.

In contrast to the interday studies different studies put also an emphasis on the intraday behavior of the interest rate on the e-MID market in the recent years. The studies conducted by Angelini

[39] Barucca and Lillo (2018) show the effects of the European sovereign debt crisis in the time of 2010- 2014 on the e-MID market. Among other aspects they show, that the volume per day drops even more in this time period.

(2000) and Baglioni and Monticini (2008) focus on the estimation of an intraday interest rate before the outbreak of the crisis in 2007. The studies by Baglioni and Monticini (2010) and Baglioni and Monticini (2013) estimate the intraday interest rate by taking into account the outbreak of the financial crisis. Until that point, all models were based on linear regressions. Demertzidis and Jeleskovic (2016) and Jeleskovic and Demertzidis (2018) used nonlinear models for the estimation of the spot intraday yield curve (SIYC) and argued that one has to move away from the assumption of a linear intraday interest rate, which becomes even more feasible after the outbreak of the crisis.

Previous research studied the behavior of interest rates on the intraday frequency highlighting some interesting methodological and theoretical aspects. However, other important variables on the e-MID market, meaning the number of transactions and volume (absolute and mean per transaction), have not been thoroughly examined yet.[40]

Yet, these two variables are important for the understanding of an interbank credit market in general, since our understanding of these markets is quite limited and more findings in this area of research could be helpful for the understanding of the behavior of banks on the ON segment of the interbank credit market. In addition, the results of an intraday analysis are important also for the optimization of the trading strategies of banks. If e.g. the volume is low during some time intervals in the day, this has also an effect on the volatility of the interest rate and thus also on risk (Engler and Jeleskovic, 2016). Furthermore, banks could optimize their activity in the market by looking more closely at the distributions of these variables during the day.

As pointed out also by Beaupain and Durré (2008) the analysis of variables in the intraday domain could reveal some interesting market dynamics. The interbank market is the first transmission channel of monetary policy. Thus, based on the analysis of these two variables, the ECB could analyze the impact of its conventional and unconventional policies on the interbank market and thereby optimize them in the future. This identification of intraday dynamics could help central banks to intervene on the interbank credit markets, which could reduce systemic risk in the financial system as a whole (Kobayashi et al., 2018).

Furthermore, these variables, also on the intraday frequency, play an important role in further empirical econometric analyses. For example, Demertzidis and Jeleskovic (2016) and Jeleskovic and Demertzidis (2018) show that estimating an intraday yield curve generates better

[40] Other important variables include the volatility and bid-ask spread within the order book but will be left for further research.

results when the number of transactions and the volume of transactions within the day can be considered as high. Therefore, findings in this research could be used from a methodological point of view for further studies using e.g. agent based modelling. Additionally, the recognition of recurrences in these distributions would allow us to implement further empirical or econometrical models in order to explain these phenomena. Last but not least, distortions in these markets also have an impact on the real economy. As already described, the interbank market is an important source of liquidity for banks, which pass on these loans to consumers and companies. If there are problems with lending, this also has real economic effects.

Some studies already analyzed the intraday behavior of these two important variables, e.g. Hartmann et al., (2001) who focus on the distribution of the volume in the period of 1999-2000 and Beaupain and Durré (2008) who focus on the volume and number of transactions in the period of 2000-2007.[41] However, to the best of my knowledge, no study has taken into account the changes of the distributions of the number of transactions and volume by comparing credits which have been sell initiated and buy initiated on different markets states. These different market states are of high importance, since the market has gone through systematic changes after the outbreak of the financial crisis. Hence, these are the main objectives of this paper:

First, my aim is to examine and discuss the intraday distribution of number of trades and volume (absolute and mean per transaction) by differentiating sell and buy transactions. Second, to analyze and discuss these distributions in different market states around major events of the financial crisis in 2007. Third, to highlight possible recurrences in the time series of the number of transactions and the volume on an intraday domain. These findings could then be used in order to estimate further empirical and econometric models (Finger and Lux, 2017).

The structure of this paper is as follows: After the introduction, I present a brief survey of the previous findings in this area of research, on the intraday behavior in terms of the number of transactions and the volume, either absolute or the mean per transaction. In chapter 3, I present the e-MID market briefly and the data sample used in this study. Chapter 3 also features different interday statistics of the mentioned variables in order to justify the use of the different periods and market states. In chapter 4, I analyze the distribution of the number of transactions in the different market states. In chapter 5, I focus on the volume and its distribution during the day. Section 6 is the conclusion.

[41] For further details of these studies see session 3.2.

3.2 Previous findings

As stated, only a few studies put emphasis on the intraday behavior of different important variables on the e-MID market, especially the volume and the number of transactions. The interest in research has recently grown exponentially, like the general interest in the interbank credit markets, especially after the outbreak of the financial crisis of 2007.

Besides the analysis of the intraday behavior of the interest rate, Angelini (2000) also shows the distribution of the trading volume during the day for the period of 01.07.1993 until 31.12.1996. His data set includes the hourly means of the volume from the time band of 08:00-09:00 until 16:00- 17:00. The time band of 17:00- 18:00 is excluded in his analysis. In terms of volume, he finds that in the morning the traded volumes in the first time band are low, are rising from 09:00 until 13:00 but drop in the next hour (due to the noon and lunchbreak effect) and rise again for the next two hours. At the end of the day, they are again almost zero at the last time band between 16:00-17:00 Therefore, this form of volume distribution can be described as U-shaped[42] around the interval of 13:00-14:00 with almost no volume traded at the beginning and the end of each day in the sample period. Angelini (2000) argues that, this kind of trading activity is mainly driven by the specific arrangements of the Italian clearing system and the behavior of banks that increase their operations at the end of the day in order to adjust their liquidity positions due to revised forecasts of their balance sheets during the day.

Hartmann et al. (2001) focus on different aspects of the e-MID market on different maturities, including also the intraday frequency. For their analysis, they use a data sample in the period between 01.11.1999 and 31.03.2000. They exclude different days, like the end of the maintenance period and the week between Christmas and New Year. For their analysis, they use one-hour intervals of different interbank variables. By focusing on the distribution of the volume and the number of transactions during the day, they find out, that these distributions follow a U-shape. The authors show, that both of the variables are low in the morning, start to rise during the time of 09:00-10:00 and reach their maximum. After this time, they observe a decline with the lowest value being in the interval of 13:00- 14:00. After this interval, the variables rise again until the interval of 16:00-17:00 and fall again after this interval until the market closes at 18:00.[43] Hartmann et al. (2001) argue that the main reason for high values of these variables in

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[42]Other authors call this kind of distribution double U-shaped.

[43] These distributions can be found on all days except Thursdays when the meeting of the governing council of the ECB take place.

the morning are mainly driven by news which have been accumulated over the night. Furthermore, they argue that the reason for higher trading in the afternoon is due to the closing time of different payment systems and also due to liquidity needs of the banks in the e-MID market.

Palombini (2003) shows the intraday trading volume on the e-MID market using a sample that spans from 03.01.2000 to 30.09.2002. By using hourly means of the intraday volume, he finds that the volume exhibits a U-shape. He shows that the volume is low in the first time band, reaches its maximum in the time band between 09:00-10:00 and then declines until the time band of 13:00-14:00, which he calls the lunchbreak. After this break, the volume per interval rises again until the time band of 16:00-17:00 and drops again at the end of the day. Palombini (2003) states that these effects can be regarded on two major events during the day on the e-MID market: First, the time until 09:00 where the credit transaction of the previous business day are settled automatically and around 13:00 when cash balances from the Italian securities market are settled. Additionally, he states that these distributions do not change on volatile days, as e.g. at the end of the maintenance period.

Barucci et al. (2004) use a data sample that spans from 01.04.1999-31.08.2001. The authors here also exclude some days in their analysis. By using one- hour intervals, they show the distribution of the volume and the number of trades during the day. They discover, that the values of these variables are relatively low at the beginning of the day, rise afterwards in the interval of 09:00- 10:00 and decline again until 14:00, where the minimum can also be found. Afterwards the distribution starts to rise again until 15:00 and drops again until the market closes. The distributions can therefore also be characterized here as U-shaped. The authors put furthermore focus on the difference between different days during the week, but the distributions remain qualitatively the same. The authors claim, based on these distributions the reasons provided by Angelini (2000), can therefore be verified.

Beaupain and Durré (2008) focus on different aspects of intraday und interday patterns of different variables. These also include the number and volume of transactions and the mean volume per transaction on the e-MID market. At the center of their attention is also, among other aspects, the identification of the changes of the operational framework of the Eurosystem after March 2004. Their data sample consist of ON transactions in the market between 04.09.2000-03.05.2007. In their study they use 30- minute intervals of the different intraday variables by also differentiating buy and sell transactions. For the purpose of their analysis, they construct two data samples, one before the 10th of March 2004 and one after this date. However, here also different transactions are removed from the data sample. The authors claim that in the intraday frequency there is clear evidence for intraday patterns. In their analysis, they showed that the distribution of the number of transactions and the volume of transactions is U-shaped with highs in the morning and in the afternoon with the lowest point of the distribution during lunchtime. For the first data sample, they found that the total volume is low at the beginning of the day, reaches its maximum at during the interval of 09:30 and starts to drop afterwards until 14:30. After that point, it starts to rise again with high values during 15:00 and 17:00. After that time, it decreases again until the market closes. During the second data sample, the distribution of volumes looks the same way with minor differences in the intervals of 15:00- 16:30. In both samples, the distributions of buy and sell transactions are quite similar. Beaupain and Durré (2008) state that the distribution of the number of transactions is almost the same as it is in the case of the volume in both cases. The distributions of the sell and buy transactions also have the same shape here. For the mean volume per transaction, the authors find a distribution with three peaks: The first at the opening of the market, the second at around 14:00 and the third high at around 17:30. In the first data sample, the order of the highs is 09:00, followed by 17:30 and the smallest high value at 14:00. In the second data sample authors find a small change, since the highest value is the one at the end of the day and not in the morning. Furthermore, here the distributions have the same distributions for buy and sell transactions in both samples. Small differences between the values of buy and sell are mainly seen in the morning when the market opens. Beaupain and Durré (2008) argue that these distributions are likely to reflect the uncertainty of the banks due to price movements in the financial markets and the availability of liquidity in the afternoon.

Iori et al. (2008) focus mainly on network aspects of the e-MID market. They also show the intraday distribution of the volume in the market during the period of January 1999 to December 2002. By doing so, they found that the distribution has a U-shape with two peaks, the first in the morning at around 10:00 and the second in the afternoon at 15:00. The authors argue that the peak in the morning can be explained by the fact that pending payments from the previous day must be repaid at around 09:00 and that in the afternoon banks settle mainly interbank and other financial payments.

Brunetti et al. (2010) use a data sample from 02.01.2006 until 01.04.2008 by taking into account in detail the ECB interventions after the outbreak of the financial crisis in August 2007. In their analysis, they put focus on a higher frequency than the previously mentioned studies, meaning five-minute intervals for different (self-constructed) intraday variables. Based on the volume per interval, which the authors call “intra-daily average trading volume” they found that the market activity is quite low at the beginning of the day and grows rapidly after 08:30. Before the outbreak of the financial crisis, the authors find a peak of the volume at around 09:30, and after the outbreak of the crisis, the peak moves to 09:45. After these time bands, the intraday volume declines until between 13:15 and 14:15 and starts to rise again until the time interval of 16:45. After this time interval, it falls again until the time when the market closes. Furthermore, they find that the values of these measures are higher for sell transactions. Their study gives interesting insights into the e-MID market, although they give no possible explanations for these distributions.

Cassola et al. (2010) focus also on different intraday variables on the e-MID market using a sample that spans from July 2007 to March 2008 in order to capture also the impact of the outbreak of the financial crisis of 2007. In their analysis, they use half-hour intervals. During the study, they focus also on the distribution of the intraday volumes and the intraday number of transactions. For the intraday volume, they argue that the distribution follows a U-shape. The market activity is high in the morning until 10:00, is relatively low in the mid-day and is higher again in the afternoon during the time of 16:00-17:00. The authors argue that this shape in the morning is mainly driven by the late liquidity shocks of the previous day. The closing of different payment systems and the liquidity needs of banks mainly affect the shape in the afternoon. During their study, they show some interesting insights into the market, meaning that these distributions have not changed significantly after the outbreak of the crisis. However, they remove different time intervals, meaning the first and the last interval of each day. Furthermore, in their analysis, they exclude different days like the first and last day of the reserve maintenance period proposed by the ECB or when the ECB conducted their main refinancing and also fine-tuning operations. Cassola et al. (2010) may focus to a small extent on the differentiation of buy and sell transactions, but do not show different distributions of intraday variables. They show only the difference between buy and sell transactions during their data sample.

Vento and La Ganga (2009b), using a data sample which spans from 01.01.2005 until 30.06.2009, show also the distribution of the intraday volume on the e-MID market. By using hourly means of the intraday volumes, they also find that the distribution has a U-shape with low trading volumes after the market opens and a rise in the interval of 09:00-10:00. During this interval, the intraday volume reaches its first peak. The authors then show low trading activity at noon and then a second peak in the afternoon at around 16:00 to 17:00, even though the second peak is lower than the one in the morning. This distribution relies on the imbalances from transactions which have not been regulated during the night. This phenomenon explains the peak in the morning. The authors argue that the peak in the afternoon relies on the European banking federation deadline, at which banks post lending quotes at the rate of the EURIBOR (Vento and La Ganga, 2009b).

Fricke (2012) uses a data sample from 01.01.1999 until 31.12.2015 and focuses mainly on network aspects of ON transactions on the market. Nonetheless, he also shows the fraction of trades occurring during the day, based on the fraction of trades occurring at a certain time during the day (based on hourly means). By doing so, he finds that the distribution of trades follows a two- hump U-shape. The number of credits are low in the time band between 08:00-09:00, rise until 10:00 and then fall until 14:00. After that time, the number of transactions again rise until 16:00 and fall until the market closes. In addition, Fricke (2012) gives some interesting insight into the distribution of the variable but does not distinguish between different periods in his large data sample nor gives explanations for these.

Raddant (2014) shows the distribution of the number of trades during the day based on a histogram of the number of trades during the day. Using a sample, which spans from 1999-2010, he shows that the distribution can be described as a U-shaped distribution, meaning that there are two high points in the distribution of the number of transaction in the e-MID market. The first one is in the morning at around 09:00 and the second one is at around 16:00, whereas the lowest number of trades can be found at around lunchtime at 14:00. Nor does Raddant (2014) give further explanations about this kind of distribution.

Engler and Jeleskovic (2016) focus on intraday credits based on higher frequency data, meaning 5-minute intervals, by using a data sample from 01.10.2005 until 31.03.2010. In their analysis, they found, among other aspects, that the intraday demand for liquidity on the e-MID market as measured by the seasonality of volume per trade follows a U-shape. Furthermore, they found evidence that the highest volatility of these measures can be found directly after the opening of the market and before the market closes at each day.

In order to conclude for the related literature, these studies can be divided into three major categories: First, these who do not put an emphasis on the outbreak of the financial crisis and focus more on the operational framework of the e-MID market, namely the studies by Angelini (2000), Hartmann et al. (2001), Palombini (2003), Barucci et al. (2004), Beaupain and Durré (2008) and Iori et al. (2008). Second, those who analyze the different distributions by taking into account the outbreak of the financial crisis, namely Cassola et al. (2010), Vento and La Ganga (2009b) and Engler and Jeleskovic (2016). And third, the studies conducted by Fricke

(2012) and Raddant (2014), who use quite large data samples which also include the outbreak of the financial crisis, but not taking into account the changes of market due to this aspect.

The most important aspects of the studies are summarized in table 3.1.

Table 3.1: Summary of the related literature of distributions in the intraday domain

Study	Data sample	Frequency	Important findings	Arguments for the shape of distributions
Angelini (2000)	01.07.1993 - 31.12.1996	One Hour	Volume U-shaped with high values in the intervals of 09:00 and 15:00-16:00.	Italian clearing system and adjustment of liquidity positions.
Hartmann et al. (2001)	01.11.1999-31.03.2000	One hour	Volume U-shaped with high values in the intervals of 09:00- 10:00 and 15:00- 16:00.	News which have been accumulated over the night and closing time of different payment systems.
Palombini (2003)	03.01.2000-30.09.2002	One hour	Volume U-shaped with high values in the intervals of 09:00- 10:00 and 15:00- 16:00.	Transactions of the previous business day and cash balances from the Italian securities market are settled.
Barucci et al. (2004)	01.04.1999-31.08.2001	One hour	Volume and number of trades U-shaped with high values in the intervals of 09:00-10:00 and 14:00-15:00.	Authors state they are in line with the study by Angelini (2000).
Beaupain and Durré (2008)	04.09.2000-03.05.2007	30- minutes	Distributions of volume and number of transactions for buy and sell follow a U-shape with peaks at 09:00- 09:30 and the intervals of 15:00-17:00. For mean volume per transaction: Distribution with three peaks at 09:00, 14:00 and 17:30.	Uncertainty due to price movements in the financial markets and the availability of liquidity.
Iori et al. (2008)	01.01.1999-31.12.2002	Not known	U-shaped volume distribution, with peaks at the intervals of 10:00 and 15:00.	Pending payments from previous days and settlement of interbank and other financial payments.
Brunetti et al. (2010)	02.01.2006-01.04.2008	5-minutes	U-shaped volume distribution with peaks at 09:30 and 16:30 before the outbreak of the crisis and at 09:45 and 16:45 after the outbreak of the crisis.	No explanations due to focus on other aspects.
Cassola et al. (2010)	01.07.2007-01.03.2008	30- minutes	Volume and number of transactions follow a U-shape with peaks in the interval of 10:00 and 17:00.	Liquidity shocks of the previous day, closing systems and liquidity needs.
Vento and La Ganga (2009b)	01.07.2007-30.06.2009	One hour	U-shaped volume with peaks in the intervals of 10:00 and 17:00.	Unbalances from transactions during the night and European banking federation deadline.
Fricke (2012)	01.01.1999-31.12.2015	One hour	U-shaped volume with peaks in the intervals of 10:00 and 16:00.	No explanations due to focus on other aspects.
Raddant (2014)	01.01.1999-31.12.2010	Histogram	U-shaped volume with peaks in the interval of 10:00 and 16:00.	No explanations due to focus on other aspects.
Engler and Jeleskovic (2016)	01.10.2005-31.03.2010	5-minutes	U-shape seasonality in Volume per trade and trade intensity.	Different explanations of intraday seasonality.

Based on section 2 of this paper, I can therefore state that the most studies use one-hour intervals in their analysis and cut off different intervals, due to methodological aspects. Furthermore, in these studies, some authors give some explanations for the distributions of the intraday variables and others show it only in a graphical way without giving theoretical explanations. Moreover, only the study conducted by Beaupain and Durré (2008), and to a less extent the studies by Brunetti et al. (2010) and Cassola et al. (2010), differ between buy and sell transactions.

With respect to the distribution of the number of transactions and the volume of transactions, I can state that all studies found the same shape of the distribution, namely a U-shaped distribution. For the volume and the number of transaction all have a U-shape with high values around 09:00-10:00 and mainly 16:00 before the outbreak of the crisis. After the outbreak of the crisis, the second peaks can be found in in the majority of studies during the interval of 17:00. Brunetti et al. (2010) conducted the only study which showed this movement of the distribution after the outbreak of the crisis. The only study which put focus on the distribution of the mean volume per transaction, is the one by Beaupain and Durré (2008), finding three peaks in the distribution, namely in the morning, around noon and before the market closes.

These U-shaped distributions of the number and volume of transactions can be found also on other segments on of the financial market. Regarding other overnight interbank credit markets, e.g. Bartolini et al. (2005), show these kinds of distributions, with minor differences, for the overnight federal funds rate in the US. The intraday analysis of the distribution of volume and number of transactions has also been carried out for different stock markets. Various studies focus on the stock market in the United States, e.g. Jain and Joh (1988) and Foster and Viswanathan (1993) show that the intraday volume on the New York Stock Exchange (NYSE) market also follows a U-shape. Ozturk et al. (2017) find clear evidence for a U-shape distribution of intraday volume and the number of intraday transactions by analyzing 50 companies listed in the S&P 500 stock market. Gurgul and Syrek (2017) find clear evidence of a U-shaped volume distribution for the majority of the companies listed in the DAX. The authors furthermore found out this trend is also observable for different companies in the Austrian and the Polish stock market. Moreover, on derivate markets, there are clear dynamics of intraday volume and number of transactions. Iwatsubo et al. (2018) e.g. show these distributions for gold and platinum futures at the stock exchange markets in Tokyo and New York. Additionally, on the market of cryptocurrencies Eross et al. (2019) found that there is an intraday distribution of volume during the day. They found that the distribution might be characterized as n shaped, meaning low values at the beginning of the day, high values in mid-day and lower values at the end of the day.

3.3 The e-MID

The object of this chapter is to present briefly the e-MID market and the general data set structure which is commercially available via the company e-MID S.p.A.

The e-MID market was founded in 1999 as an initiative of the Bank of Italy. On the e-MID market credits with a maturity from ON until one year can be traded and the market functions on the principle of the limit order book. The minimum volume of each credit transaction equals 50,000 euro.[44] The market opens at each trading at 08:00 and closes at 18:00 in the afternoon.

The data sample I use for the purpose of this paper includes all euro denominated credit transactions from 03.10.2005 until 30.03.2005 and includes 1,149 business days with a total number of credits of 426,392 credit transactions of different maturities. Out of these, 377,745 transactions are ON credits and 48,647 are the remaining credits with different maturities. Thus, in this sample period about 89% out of all credit were transactions on the ON level. Arciero et al. (2016) state that a shift from longer to shorter maturities meaning ON credits was observed especially after June of 2008. After that date, more than 90 % of all credit transactions were executed during that time frame.

As seen in section two of this paper, the majority of studies base their analysis of the intraday behavior of the key variables on hourly means. Here, I differentiate my analysis also from a methodological point: I follow Beaupain and Durré (2008) and Jeleskovic and Demertzidis (2018) and use 30-minute intervals of the different variables during the day. As the authors state, the findings using means on a higher, but not too high frequency, leads to the point where the results become more precise, and the practical relevance on a lower time scale becomes even higher. Additionally, I will focus on all credits, from the opening of the market at 08:00 until the market closes at 18:00, which are ten hours, without removing any time intervals or specific days. Hence, I base my analysis on 20 30-minute intervals. For visibility reasons, the time stamp of 08:30, which is the first interval, represents the interval of 08:00-08:30 and the time stamp of 18:00 represent the last interval of 17:30- 18:00 and so on.

The data structure which I have obtained is presented in table 3.2.

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[44] Even though the credit transactions may be allocated in other currencies, including the pound, the dollar and the polish Zloty, the main currency is the euro.

Table 3.2: Data structure of the e-MID market

Market	Duration	Date	Time	Rate	Amount	StartDate	EndDate	Quoter	Aggressor	Verb
TRAS_EUR	ON	03.10.2005	08:55:23	2.085	150	03.10.2005	04.10.2005	IT0271	IT0265	Sell
TRAS_EUR	ON	03.10.2005	09:05:29	2.08	115	03.10.2005	04.10.2005	IT0258	IT0271	Buy
TRAS_EUR	ON	03.10.2005	09:05:58	2.09	25	03.10.2005	04.10.2005	IT0259	IT0164	Buy

Market: Indicates the currency used for the credit transaction. On the e-MID market, transactions are mainly denominated in euros. As stated, all transactions observed for the purpose of this paper are denominated in euros.

Duration: Indicates the duration of each traded credit. Current maturities range from overnight credits with a maturity of one day, different weekly maturities, different monthly maturities and up to maturities with one year. Based on the duration, some credits have "broken dates" which means that the exact maturity of these credits is not known. These kind of credit transactions represent only a very small number of transactions.

Date: Indicates the date when the credit was executed between the two banks.

Time: Provides the exact time when the credit transaction was executed.

Rate: Represents the interest rate of the respective credit.

Amount: Indicates the credit amount of the respective credit in millions of euros.

StartDate: Specifies the start date of the credit transaction.

EndDate: Identifies the end date of the credit. On this date, the bank that acts as the borrower must repay the credit to the lending bank. In the case of ON credits, the repayment day is the next business day as has been already stated. However, the exact time of credit repayment also depends on whether the borrower or the lender is an Italian bank. In this case, the time of credit repayment is 09:00 on the end date of the credit. If the credit is conducted between two non-Italian banks, the time of repayment is 12:00. Based on these facts, the repayment time for ON credits is the next business day, at either 09:00 or 12:00.

Quoter: This is the bank that issues the contract of borrowing or lending in the order book.

Aggressor: Represents the active bank that chooses the credit request (lending or borrowing) from the order book.

Verb: Displays the type of transaction from the perspective of the aggressor. The verb "sell" means that in this case, the aggressor sells a credit to the quoter. Thus, this transaction can be called a sell transaction. The verb "buy" means that the aggressor borrows money from the quoter bank. Thus, this transaction can be called a buy transaction.

The representation of the general dataset of the e-MID shows that different information regarding the executed credit transactions for both market participants and non-market participants is available. However, information that is not freely available to non-market participants also exists. This includes, on the one hand, the exact names of the transaction partners. As already presented, both quoter and aggressor are displayed. This display includes a five-digit identification code consisting of two letters and three digits. The two letters reflect the country of origin of each bank and the three digits represent a specific bank code. The exact names of the banks are not identified. Additionally, the system does not display the exact time when a particular credit request (buy or sell) from the quoter bank was entered in the order book. Neither date nor time of the setting in is specified, so it is not known how long a credit request was listed in the order book before it was executed. Neither credit inquiries from quoter banks that were not selected by aggressor banks from the order book are freely available. Another important piece of information that is not freely available on the e-MID market is the exact repayment time of the credit. It is not possible to tell at what time a bank has repaid a specific credit. Hence, only the maximum maturity of repayment is known. Additionally, banks may refuse a specific credit transaction in the e-MID market (Iori et al.,2015). The number of these refused credit transactions is also unknown. By knowing this number, further analyses regarding the perceived risk profiles of each bank could be executed.

As stated, the interest of this paper does not only rely on the different descriptive statistics, but on their differences in different market states. Therefore, following different studies e.g. Gabbi et al. (2012) and Demertzidis and Jeleskovic (2016), I also divide my data sample into different subsamples which represent different market states.

Many studies show that different reasons play a role in the declining of interbank transactions after the outbreak of the financial crisis of 2007 and the de facto interbank market freeze after the collapse of Lehman Brothers. Freixas and Jorge (2008) e.g. show that the main reason for this fact is the increase in counterparty risk. On the other hand, Ashcraft et al. (2011) argue that an important reason also lies in the reality of liquidity hoarding. Brunetti et al. (2019) focus more on the interconnectedness between banks in order to understand this phenomenon.

The first period is equal to 473 business days and ranges from 03.10.2005, the beginning of the data sample until 08.08.2007, one day before the outbreak of the financial crisis of 2007. This period can be called the "pre-crisis" period where the number of transactions and the volume of transactions is steadily increasing. Here, the market mechanism is functioning very well, meaning that the allocation of liquidity between banks is given.

The second period equals 281 business days and ranges from 09.08.2007, the day of the outbreak of the financial crisis of 2007 until the 14.09.2008, one day before the collapse of the investment bank Lehman Brothers. In this period, the number of transactions and volume of transactions (and the number of active banks participating in the market) are starting to decrease. This period is the "first-crisis period", although the market is still functioning.

The third period which is 166 business days long, ranges from 15.09.2008, the day of the Lehman Brothers collapse until the 12.05.2009 one day before the ECB reduces the key interest rate for the last time. During this period, the number and volume of transactions are decreasing even more, a fact that is also observable for the number of active banks in the market. This period is called the "second-crisis period" where the market does not function properly anymore, meaning that the liquidity provision between banks is disturbed. During this period, banks with liquidity surpluses search for other markets in order to find investment opportunities and banks with liquidity shortages rely more on the provision of liquidity from the ECB.

The last period is 229 business days long and ranges from 13.05.2009, the day of the last ECB key interest rate reduction until the end of the sample period at the 31.03.2010. In this period, the number and volume of transactions as the number of active banks is even lower compared to the other periods. Here again, the market does not function well anymore and the main source of liquidity is given by the ECB. This period can be called the "after- crisis period".

The different sub-periods are summarized in table 3.3.

Table 3.3: Presentation of the sub-periods

Period 1	03.10.2005-08.08.2007	Period before the crisis
Period 2	09.08.2007-14.09.2008	Outbreak of the crisis until the collapse of Lehman Brothers
Period 3	15.09.2008-12.05.2009	Lehman Brothers collapse until reduction of key interest rate
Period 4	13.05.2009- 31.03.2010	Key interest rate reduction until the end of the observation period

The descriptive statistics regarding the interday frequency reveal following facts: During period 1, the pre-crisis period, the absolute number of transactions is 24,342 buy transactions and 75,928 sell transactions, whereas the mean number of transactions per day is equal to 99.06 buy transactions and for the sell transactions this value is equal to 302.95. In this period, the liquidity provision between banks with surpluses and banks with short-term cash needs is functioning well.

By taking into account period 2, I can state that the absolute number of transactions equals 24,342 buy transactions and 75,928 sell transactions. The mean number of buy transactions per day equals 86.62 and the mean number of sell transactions equals 270.2. Thus, the pre described drop in the number of trades per day is visible even though this trend is not so dramatic as it will be in the next periods. Still, as this is now in the first period of the crisis, the market is still functioning well.

The third period of the data sample, consists of 8,774 buy transactions and 34,081 sell transactions. During this period, the mean number of transactions drops even more and the market is no longer functioning properly anymore. The mean number of transactions per day equals to 52.85 for buy transactions and the mean number of transactions for sell transactions is equal to 205.31. What I can state furthermore here is that the difference in the number of transactions between buy and sell becomes smaller, therefore, there is a noticeable shift from sell to more buy transactions.

As already stated, the fourth period is regarded as the period outside the crisis, where the market is no longer functioning well. During this period, the number of buy transactions equals 9,625 and the number of sell transactions is 34,835. In the last period, the mean of the transactions per day drops even more to 42.03 for buy transactions and to 152.11 for sell transactions.

All these pre mentioned interday descriptive statistics regarding the number of transactions are summarized in Table 3.4.

Table 3.4: Mean number of transactions per day [45]

	Period 1	Period 2	Period 3	Period 4
Buy transactions	99.06 (46,860)	86.62 (24,342)	52.85 (8,774)	42.03 (9,625)
Sell transactions	302.95 (143,300)	270.2 (75,928)	205.31 (34,081)	152.11 (34,835)

The findings of the mean volume per day (in million euros) are summarized in table 3.5.

Table 3.5: Mean volume per day in million euros

	Period 1	Period 2	Period 3	Period 4
Buy transactions	4,665.03	2,731.090	1,564.411	884.545
Sell transactions	17,099.96	11,398.338	5,833.06	3,198.772

By taking into account the findings in table 3.5, it is clear that the volume per day drops in period 2 and even more in period 3 and 4. These findings are consistent with the description of the different market states.

Furthermore, based on these means, it is apparent that the difference in terms of mean volume per day are becoming smaller from period 1 and 2 to period 3 and 4. This indicates that a shift from transactions of sell to transactions of buy in terms of volume can be observed.

The findings of the mean volume per transactions per day are summarized in table 3.6.

[45] In parentheses are the absolute number of transactions. These different numbers rely on the fact, that the sub-periods are differently long.

Table 3.6: Mean volume per transaction per day

	Period 1	Period 2	Period 3	Period 4
Buy transactions	47.86	32.19	28.68	21.95
Sell transactions	56.72	42.61	28.23	21.05

By taking into account the findings of table 3.6, it is clear that the mean volume per transactions drops during the different sample periods, especially after the Lehman Brothers collapse in period 2. This could therefore be an indicator that larger and more system relevant banks leave the market. What is also shown here is that the mean volume for buy transactions is smaller than the mean of sell transactions in period 1 and 2, but this changes in periods 3 and 4. Here the values are small for both credit types but the mean volume for buy transactions is higher than the ones of sell transactions. However, these differences are too small to be relevant from an economic point of view. One can only assume that buy and sell transactions in periods 3 and 4 become more balanced in comparison to periods 1 and 2.

Hence, these statistical facts regarding considered market variables highlight strong differences among those four market states as well as between the sell and buy credits. Now, a closer look into the intraday distributions is given.

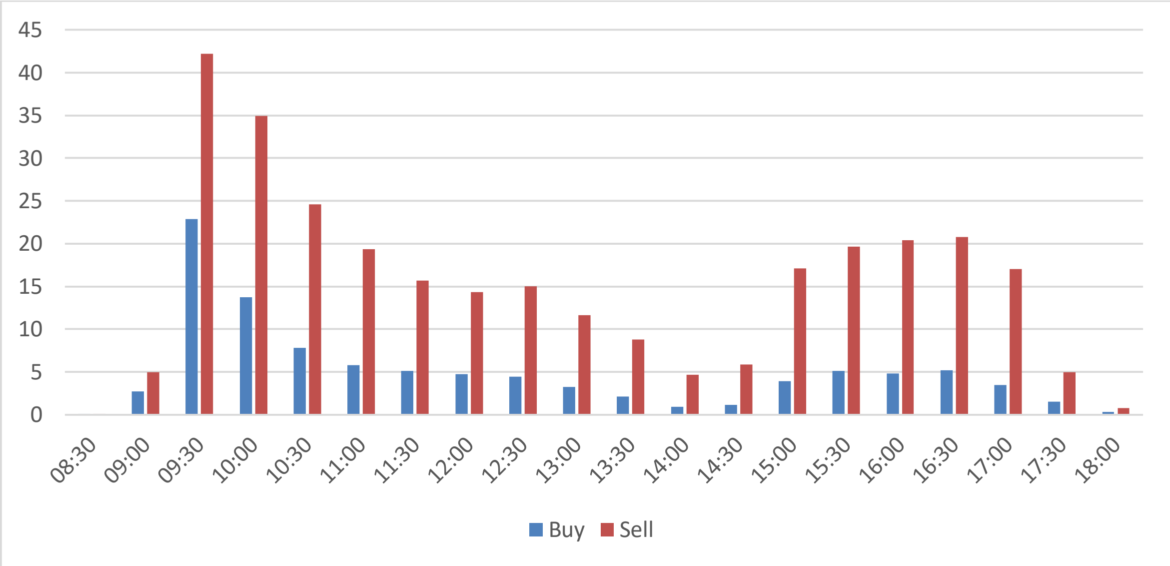
3.4 Empirical results: Transactions

As already stated, in the center of interest of this paper are not only the distributions of the different variables but also to take into account the difference between the buy and sell initiated credit transaction in different market states.

In this section, I focus on the distribution of the number of transactions differentiated in buy-sell and in the different periods. Due to the fact that the previously mentioned periods are differently long and in order to capture this fact, the mean number of transactions per interval will be shown during this chapter. In order to visualize the effect of the intraday distribution of the variable of interest, I summarize all credit transactions of each specific time interval during the day and divide this number with the number of days of each period. In the end, I show these intraday distributions distinguishing over for the different periods which are defined above.

The results of the distribution of the number of transactions are shown in figures 3.1-3.4. In order to see exactly the difference between the buy and the sell initiated transactions, I show the distribution of both in one figure for each sub-sample period.

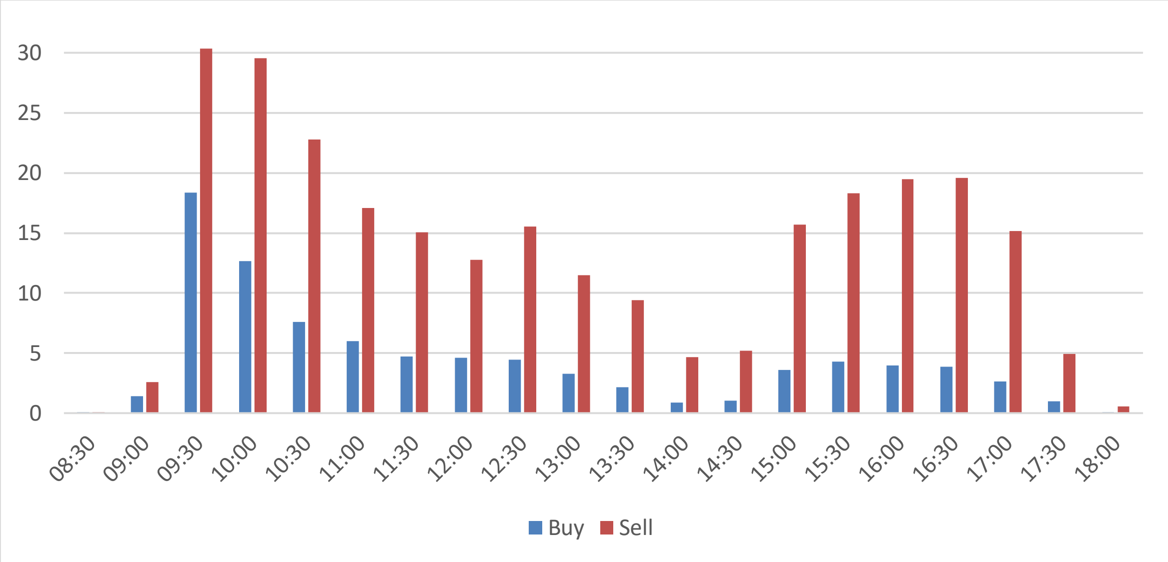
Figure 3.1: Mean number of transactions per interval in period 1



As can be seen in figure 3.1, in the first period the number of transactions in the first interval are low, reach their maximum in the interval of 09:30 and then drop until the interval of 14:00, with a small rise during the intervals of 12:00-12:30. From 14:00, the number of transactions rise again until the interval of 16:30 when they begin again to fall again until the market closes at 18:00. These trends are exactly the same for the buy and the sell transactions, with a small difference around noon. The distribution of the number of transactions can be described here as U-shaped, or a shape with two humps (m- shaped) when taking into account the low values at the beginning and the end of the day. The first hump is found at 09:30 and its second-high value in the interval of 16:00 and 16:30, with a low point during the interval of 14:00. What is also obvious is that the number of sell transactions is higher than the buy transactions in each interval in this period.

The distribution of the number of transactions for period 2 can be found in figure 3.2.

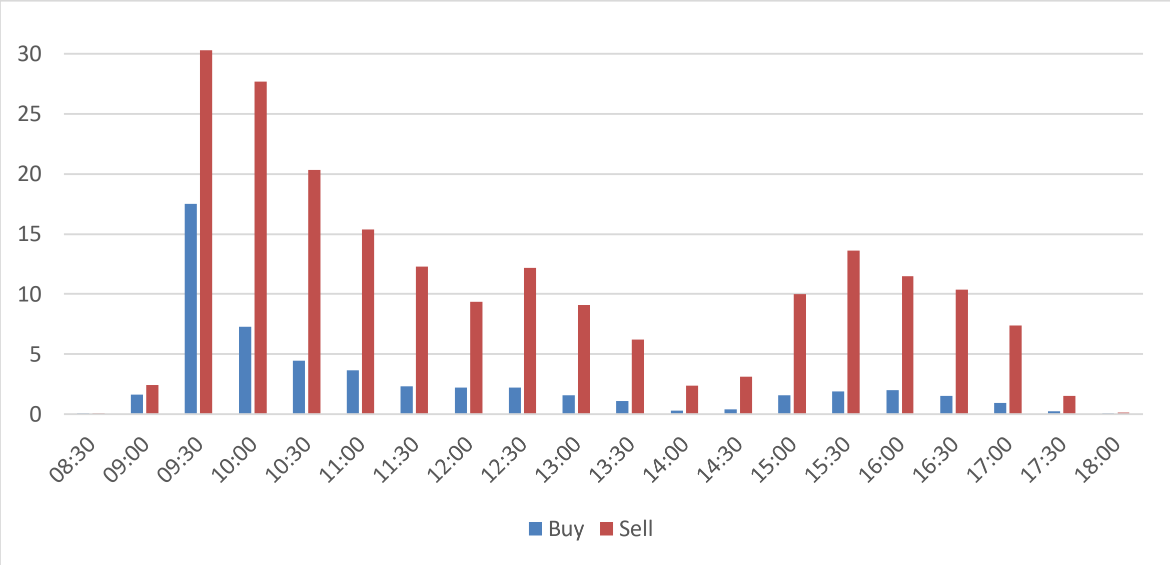
Figure 3.2: Mean number of transactions per interval in period 2



By taking a look at figure 3.2, we can see that the number of trades drops in comparison to period 2 in each interval for the sell and buy transactions. Furthermore, the distribution of the number of transactions in the first crisis period looks like the distribution of period 1. The number of transactions is low directly after the markets open and are high around the intervals of 09:30 and 10:00. From that time point, they fall again until the interval of 14:00, with a small rise during the interval of 12:30. From that time point again, the number of transactions rise again until 16:30 and drop afterwards until the market closes. Moreover, here the distribution of the buy and sell transactions have qualitatively the same shape. The difference here is, that the second hump for buy transactions can be found now at 15:30. Based on the findings in period 2, the number of transactions for sell transactions is again higher than the number of buy transactions in each interval. What is observable here, is that the gap between the values of sell and buy transactions becomes smaller in the most intervals during the day. This may highlight the fact that credit sellers begin to overthink acting on the interbank due to the general uncertainty after August 2007.

The distribution of the number transactions in period 3 can be found in figure 3.3.

Figure 3.3: Mean number of transactions per interval in period 3

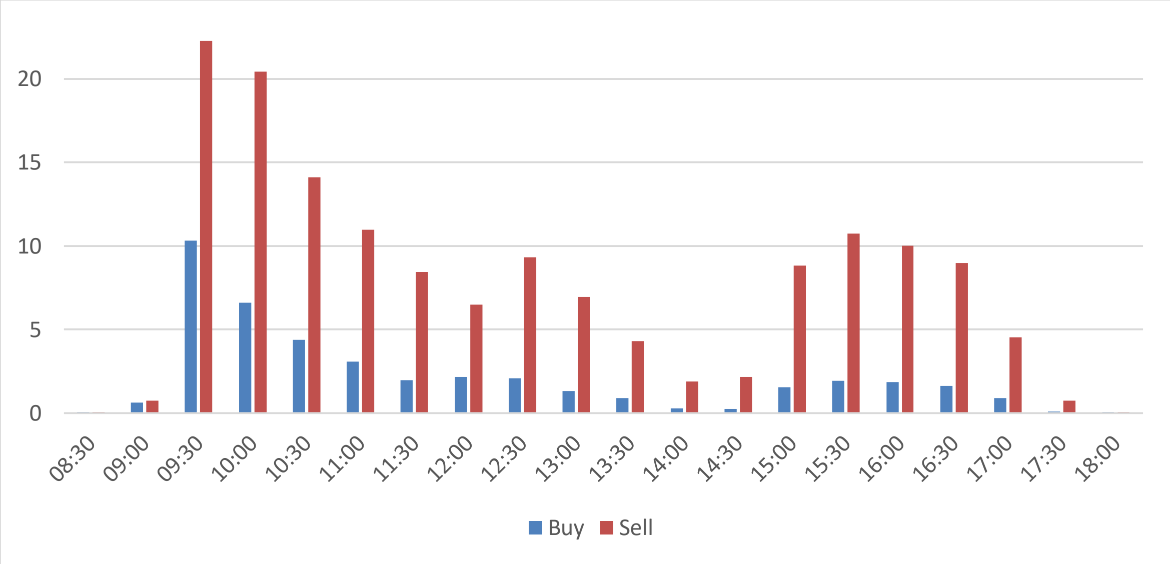


By taking a look at the distribution of the number of transactions in period three, it is visible that the number of transactions drop further more in each interval, for both sell and buy transactions. For this period, we can again state that the distribution of buy and sell initiated transactions have qualitatively the same shape, with some differences during the intervals of 15:30 and 16:00. During this period the gap between the sell and buy transactions becomes even smaller.

During this period the number of transactions is low at the start of the day and reach its maximum at the time interval of 09:30. From that point, they start to drop slowly until the interval of 10:00 and even more until the interval of 14:00, with a small rise during the intervals of 12:00-12:30. After the interval of 14:00, they start to rise again and reach their highest value during the afternoon until the interval of 15:30 for sell transactions and at 16:00 for buy transactions. After these intervals the values start to fall until the market closes at 18:00. In addition, during this period, the number of sell transactions is higher than the number of buy transactions in each interval and also a transfer from sell to more buy transactions in the most intervals can be observed.

The distribution of the number of transactions in period 4 can be found in figure 3.4. In this period only six transactions occur during the interval of 08:30 (five buy transactions and 1 sell transaction) and only 15 transactions (three buy transactions and 12 sell transactions) occur during the last of interval of 18:00 in the whole period. Hence, the first and the last interval in this period cannot be considered as representative.

Figure 3.4: Mean number of transactions per interval in period 4



Like all the aforementioned periods, the distribution of the transactions regarding buy and sell transactions have the same shape qualitatively. As in period 3, the number of transactions in this period are quite low in the beginning of the day rise in the interval of 09:30 and drop until the interval of 14:00, with one small rise at around noon. From the interval of 14:30 they rise again until the interval of 15:30 and drop again until the market closes. Thus, the distributions of the number of transactions have the same shapes qualitatively as they were in the period 3, where there the market was not functioning as well. For the buy transactions, the difference now between the intervals of 15:30 and 16:00 becomes smaller. During this period, the number of sell transactions is also higher than the number of buy transactions, whereas again a smaller gap between sell and buy transactions in the most intervals compared to the previous period is noticeable.

In order to sum up, the analysis of the number of transactions reveal some very interesting facts:

By taking into account the general distribution of the (mean) number of trades per interval, it is now clear, that in all mentioned periods and market states, the distributions can be described as U-shaped. As already described, the number of transactions are quite low during the first hour meaning that the market participants are quite inactive. One possible explanations for this fact is, that the banks monitor their liquidity needs during these intervals and optimize their daily trading strategies. The first hump can be found during the intervals of 09:00 and 09:30. The acting in the morning allows the banks to be liquid to a certain extent over the day. Possible explanations for this humps are manifold: On the one hand, the conditions of the Italian clearing system (Angelini, 2000) and the news which have been accumulated over the night (Hartmann et al., 2001), influence the behavior of banks to act early in the morning. On the other hand, the settlement of credit transactions of the previous business day (Palombini, 2003), and here especially those where no Italian bank was involved in a credit transaction, as in these cases the repayment time is 12:00 play a major role to act in these intervals. Furthermore, pending payments from previous days (Iori et al.,2008), as it the case for credit transactions with an involvement of Italian banks, influence the behavior of banks in order to act at these time intervals in the morning. Until the time interval of 09:00 the ON credits from the previous days must be repaid, so many banks become more liquid and can act after this interval more frequently, also on the e-MID market. Furthermore, imbalances from transactions during the night (Vento and La Ganga, 2009b), liquidity shocks of the previous day (Cassola et al., 2010) and the uncertainty due to price movements in the financial markets and the availability of liquidity (Beaupain and Durré, 2008), are further reasons for the banks to act more frequently during the intervals of 09:00 until the interval 10:30.

The second hump can be found during the afternoon, two to two and half hours before the market closes. Possible explanations for this phenomenon are the adjustment of liquidity positions before the day closes (Angelini, 2000), the closing time of different payment systems (Hartmann et al., 2001, Cassola et al., 2010), the time point at which cash balances from the Italian securities market are settled (Palombini, 2003) and settlement of interbank and other financial payments during this time (Iori et al., 2008).

Between these two humps, there is also one interval at which the number of transactions is increasing. This is the interval of 12:30, or as stated the time between 12:00 and 12:30. This interval represents the time before lunch. Based on this kind of increase in the values, I can thereby state that the banks become active in the market before the lunchbreak, as they may know that the market is quite inactive during and after the lunchtime. This fact should also have been taken into account when analyzing the banks behavior on the e-MID market, as it stays intact during all periods and market states. This study is the first one to detect this effect immediately before the lunch-time.

When now comparing the sell and buy distributions for this variable, it is apparent that the distributions have the same shapes as the market is functioning properly in the periods 1 and 2. This changes in the periods 3 and 4, when the market is not functioning properly anymore. Here, the hump in the afternoon for the buy transactions is earlier during the day, which can be regarded as an indicator of the greater liquidity needs of borrowing banks, as they might be concerned about their liquidity needs later in the day.

With regard to the comparison of the values between buy and sell transactions, it can be shown that the numbers of sell transactions are higher in each interval and in each period than those of the buy transactions. This aspect has also been pointed out by Beaupain and Durré (2008) for the interday frequency. This indicates that this higher activity in sell orders on the market may be caused by banks, to a large degree, in order to optimize their trading strategy when depositing larger liquidity.[46] Here in this study it is shown that this fact can be observed also in the intraday frequency in all intervals. This phenomenon stays stable over the time in the different periods and robust during the different values. It can therefore be called a stylized fact of the market (Cont, 2001, Winker and Jeleskovic, 2007). There is only a small amount of studies which focus on the findings and explanations of stylized facts on interbank credit markets. Their findings are basically found in the network formations of the market, as the studies of e.g. Craig and von Peter (2014) for the German interbank market or the studies e.g. by Fricke and Lux (2015) and Finger and Lux (2017) for the e-MID market indicate. This is, to the best of my knowledge, the first study which finds and shows a stylized fact of the distribution of the number of trades during the day on the e-MID market. Winker and Jeleskovic (2006) argue that, based on stylized facts on different segments of the financial markets, further analyses can be conducted in order to widen our theoretical understanding of the markets and in order to generate novel empirical or econometrical models. Furthermore, these stylized facts are important due to the fact that these phenomena on different segments of the financial markets are robust and must be explained. Additionally, these facts initiated different models, as it was in the case of the GARCH models for the explanation of the interest volatility (Bollerslev, 1986). Furthermore, these facts are of high interest in order to build up new estimation methods which can capture different asymmetries on the financial markets as in the case of agent based models (LeBaron, 2006) or microsimulation models (Castiglione and Stauffer, 2001 and Winker et al., 2007).

What is also noticeable in this context of the comparison of the values between the number of sell and buy transactions is, that the difference between them becomes even smaller in the most intervals from period 1 to period 4. This again means that banks are becoming more active in terms of borrowing credits. This may indicate the fact that the uncertainty of repayment when selling credits becomes larger, especially after the collapse of Lehman Brothers.

[46] Banks put rather many smaller orders than one of huge volume to not influence negatively the price of the credit which is the interest rate in this section.

3.5 Empirical results: Volume

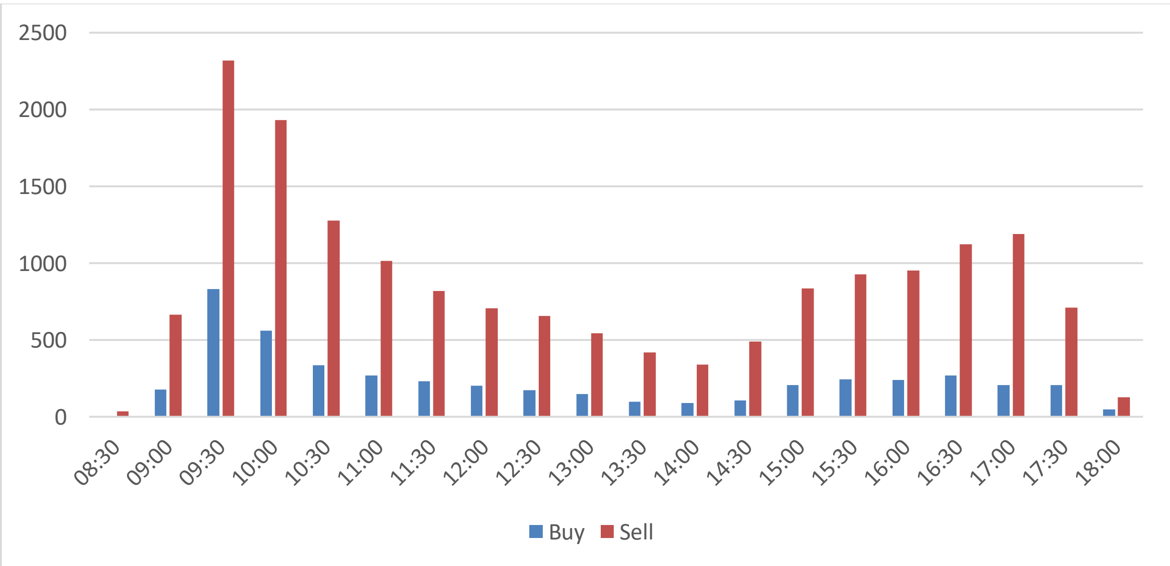
After the number of transactions, I will focus on the volume of transactions on the intraday basis. In this chapter, I divide my findings into two aspects: First, I show the distribution of the mean volume per interval during the day. In this case, again the mean and not the absolute volume per interval is again taken into account in order to capture the different long periods. For this purpose, I sum up the volumes of the transactions of each specific time subinterval during the days and divide this number with the number of days in each period. Secondly, I will focus on the distribution of the mean volume per transaction.

As in the case of the distribution of the number of transactions, I also show the volume per interval and the mean volume per transaction in each interval differentiated in buy and sell transactions in one figure.

The distributions for the mean volume per interval in million euros can be found in the figures 3.5-3.8.

Figure 3.5 shows the distribution of the mean volume per day in the first period.

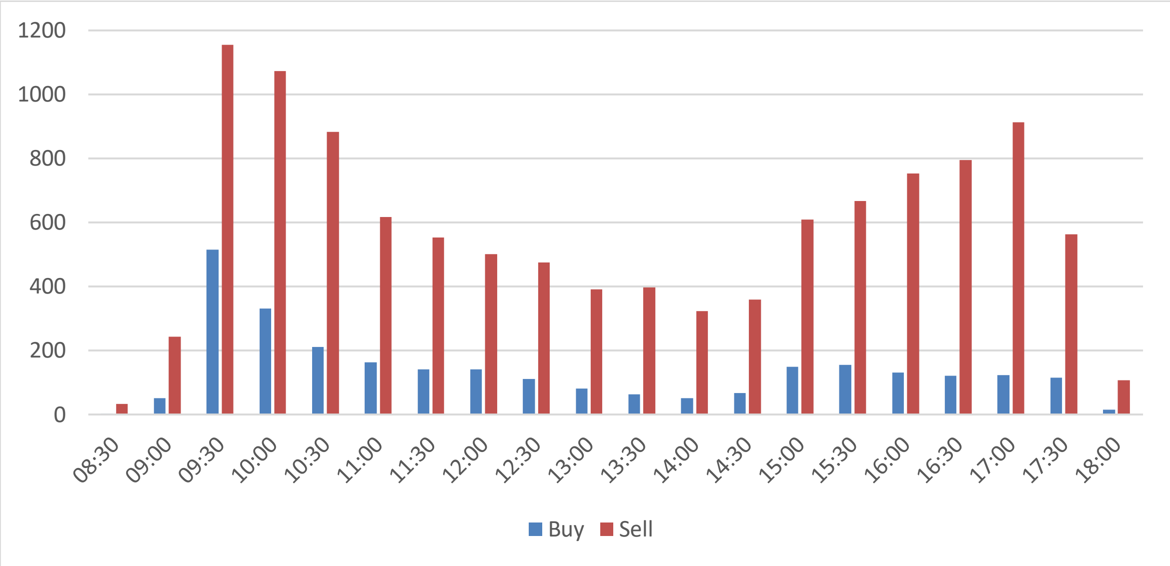
Figure 3.5: Mean volume per interval in period 1



By looking at the distribution of the intraday volume in period 1 it is noticeable that the values of the sell transactions are higher than those of the buy transactions in each interval. Furthermore, the distribution for buy and sell transactions have the same shape as it was also with the number of transactions. Here again, the distribution can be described as double-humped, or U-shaped. The volume per interval is low at the beginning of the day, rises from the interval of 09:00 until the interval of 09:30 and drops afterwards until the interval of 14:00. From that time interval, the volume rises again until the interval of 17:00 for the sell transactions and until 16:30 for the buy transactions. Afterwards it drops again until the market closes. In contrast to the number of transactions, an increase in the volume during the interval of 12:30 is not given.

The volume per interval in period 2 can be found in figure 3.6.

Figure 3.6: Mean volume per interval in period 2

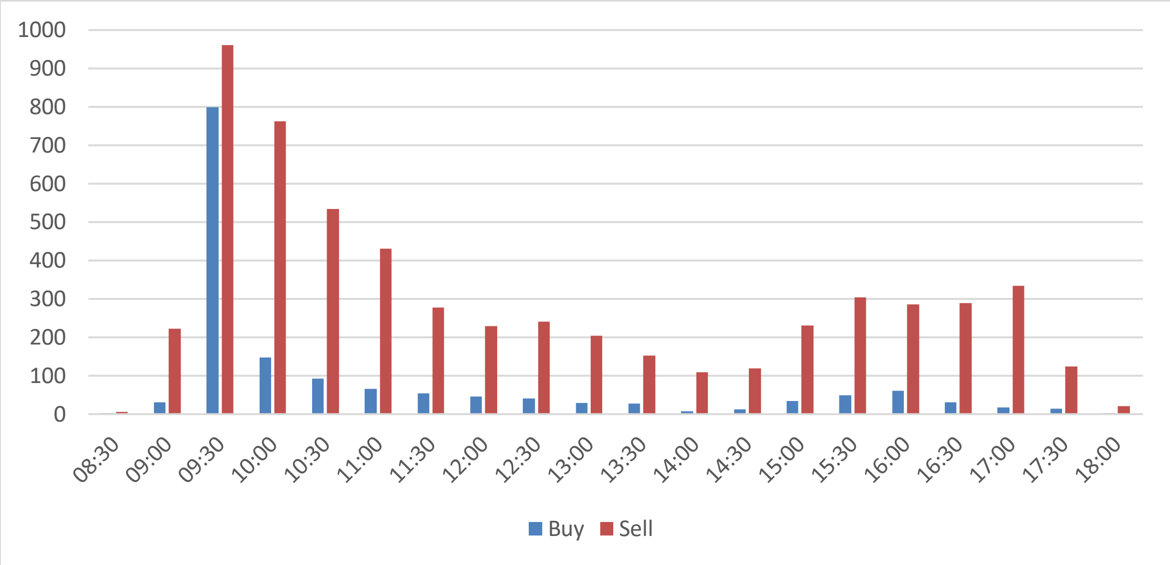


Regarding the intraday distribution of volumes in period 2, it is observed that the volumes per interval drop in each interval when compared to period 1. As in period 1, the values of the sell transactions are higher than the buy transactions in each interval. Furthermore, we can see, as it was the case for the number of transactions that the gap between sell and buy transactions is becoming smaller in this period.

Here also, the distribution of the buy and sell initiated transactions have the same shape, with some minor differences at the end of the day. The distribution can also be called in this period two-humped. Again, the distribution of volume is low at the beginning of the day, reaches its maximum at the interval of 09:30 and starts to drop until the interval of 14:30. After that time point, it rises again until the interval of 17:00 for the sell transactions and at 15:30 for the buy transactions. After these time intervals, the volume drops again until the end of the day.

The distribution of the intraday volume for period 3 can be found in figure 3.7.

Figure 3.7: Mean volume per interval in period 3

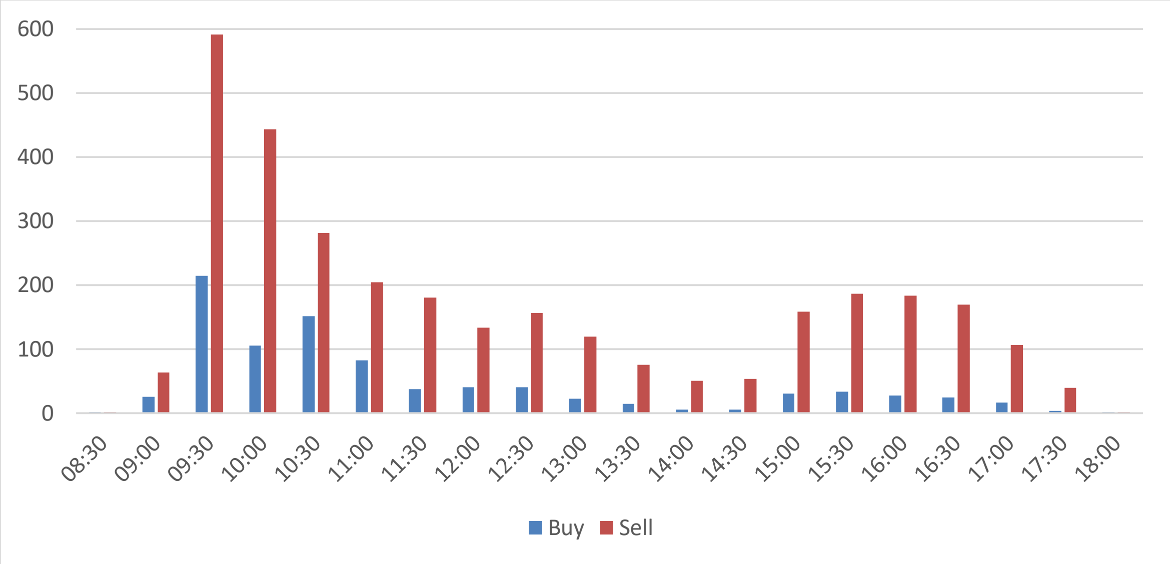


Regarding the results in period 3, we can see that the volume per interval drops even more dramatically in each interval. In this period, the values for sell transactions are also higher than the buy transactions in each interval, even though again the gap between the sell volumes and the buy volumes becomes smaller in almost each interval.

During period 3, the distributions of the volume between buy and sell transactions seem to differ now and the smoothness of the distributions differs in contrast to the previous periods. There are now not such clear distributions as it was the case for the number of transactions. However, the distributions for the sell and buy volumes may still be called two-humped. The first hump can be found for both distributions in the interval of 09:30 and the second hump in the intervals of 15:30- 17:00. What is further noticeable here is, that the second peak of the distributions differs again for the sell and buy distributions. The peak of the sell distributions can be found later in the day at 17:00 and for buy transactions at 16:00.

The distribution of the volume for period 4 can be found in figure 3.8. Due to the already stated extremely low number of transactions in the first and in the last interval of period 4 the values of the volume of transactions cannot be considered as representative as well.

Figure 3.8: Mean volume per interval in period 4



The distribution in period 4 shows that the values of the volume now are even lower than they were in the previous periods. Furthermore, the gap between the values is becoming even smaller. The distributions of the buy and sell transactions in this period do not look the same anymore and the smoothness of the distributions differs even more. In addition, during this period, the values for the sell transactions are higher in each interval than those of the buy transactions. The distributions may still be characterized in general as two humped-shaped, or U-shaped with high values in the morning in the intervals of 09:30 and 10:00 for the sell transactions and during the intervals of 09:30 to 10:30 for buy transactions. The second hump can be found during the intervals of 15:30 to 16:30.

In order to come to conclusion about the volume distribution, I can recognize some interesting facts: In general, the smoothness of the distributions differs and the recognition of patterns in the distributions becomes more difficult when compared to the number of transactions. However, in all mentioned periods, the distributions can be characterized two-humped or U-shaped, with high values in the intervals of 09:00-09:30 in the morning and high values in the afternoon. The reasons for such distributions have already been given in the previous chapter and hold for the volume of transactions as well. In contrast to the number of transactions, there is not an observable pre-lunchbreak effect.

Furthermore, there are again some similarities in the distributions in different market states. When the market is functioning properly in periods 1 and 2, the distributions of buy and sell transactions have the same shape. In these periods, however, the second peaks in the distributions also differ, meaning that the peaks of the sell and buy transactions differ. Also in these periods, the borrowing banks become more active earlier in the day than the credit lending banks. This fact highlights the aspect that the liquidity needs must be fulfilled earlier in the day, when acting as a borrower. The smoothness of the distributions changes in the periods 3 and 4 when the market is not functioning properly anymore. These changes in the smoothness of the distributions, especially when the market is not functioning properly anymore, highlights again the general uncertainty in the market. Likewise, the high values in the distributions also change. In the periods where the market is no longer functioning well, higher credit volumes can be observed earlier during the day. This also highlights the greater uncertainty in the market, as banks have to become active earlier during the day. Explanations for such distributions are the same as given in the previous sections for the number of transactions, which include pending payments from previous days (Iori et al.,2008) for the morning hump and the adjustment of liquidity positions before the day closes (Angelini, 2000), for the evening hump. This study is the first to show that higher credit volumes are executed earlier the day when the market is not functioning properly anymore.

When comparing now the sell and buy transactions, I can state that the shapes look similar in the periods 1 and 2, although the second-high values during the day differ already when the market functions properly. The distributions do not look the same qualitatively in the periods 3 and 4, which means, that, based on the volume during the day, the behavior of credit partners is different. Banks seem to behave differently when it comes to the disposition of excessive liquidity as it is the case for sell transactions and when liquidity needs are taken into account during the day, as it is the case for buy transactions.

Also interesting and noteworthy, is the fact that the volume of the sell transactions is higher than the volume of the buy transactions in each interval of the day and in each period. Thus, the previously mentioned stylized fact in the number of transactions can be observed also in the distribution of the volume. Based on these findings, I can state that banks use the market primarily in order to deposit liquidity in each interval of the day and in each period analyzed. To the best of my knowledge, this is the first study on the e-MID market which discovers this fact on the intraday distribution of the volumes.

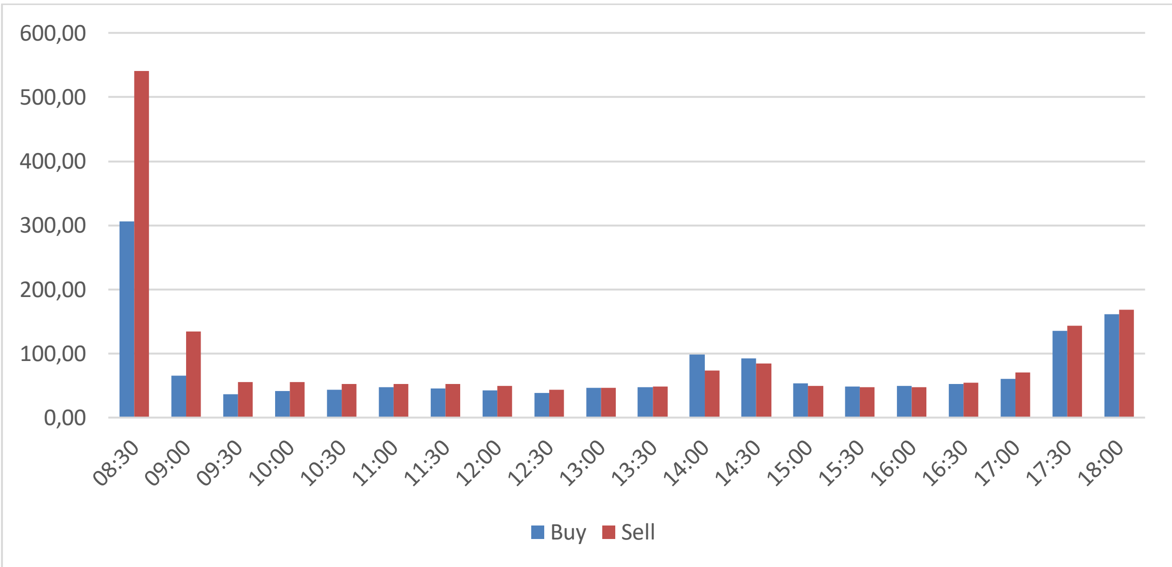
Additionally, also based on the distribution of the volumes per day, it is clear that the gap between the sell and buy volumes becomes smaller from period 1 to period 4. This means that banks use the market even more frequently as a source of liquidity, rather than as an option of depositing liquidity amounts.

One other important variable regarding the volume distribution is the mean volume per transaction of each interval in order to detect when the credit transactions were executed with high volumes during the day. This variable is of high interest due to the fact that it can influence the behavior of the banks in the e-MID market as it can indicate at which time during the day to become active for the buy and sell of credits with a high volume. Additionally, based on this variable, banks can optimize their trading strategy. Furthermore, the mean volume per transaction is frequently used in econometric models for modeling order book dynamics (Hautsch and Jeleskovic, 2008). In order to capture this variable, I sum up all volumes in each interval and in each period and divide these volumes by the specific number of trades in each of these intervals. Also in this case the values of the buy and sell transactions are shown together for each period.

The distribution of the mean volume per transaction in million euros for the different sub-periods can be found in figures 3.9-3.12.

The distribution of the mean volume per interval in the period 1 can be seen in figure 3.9.

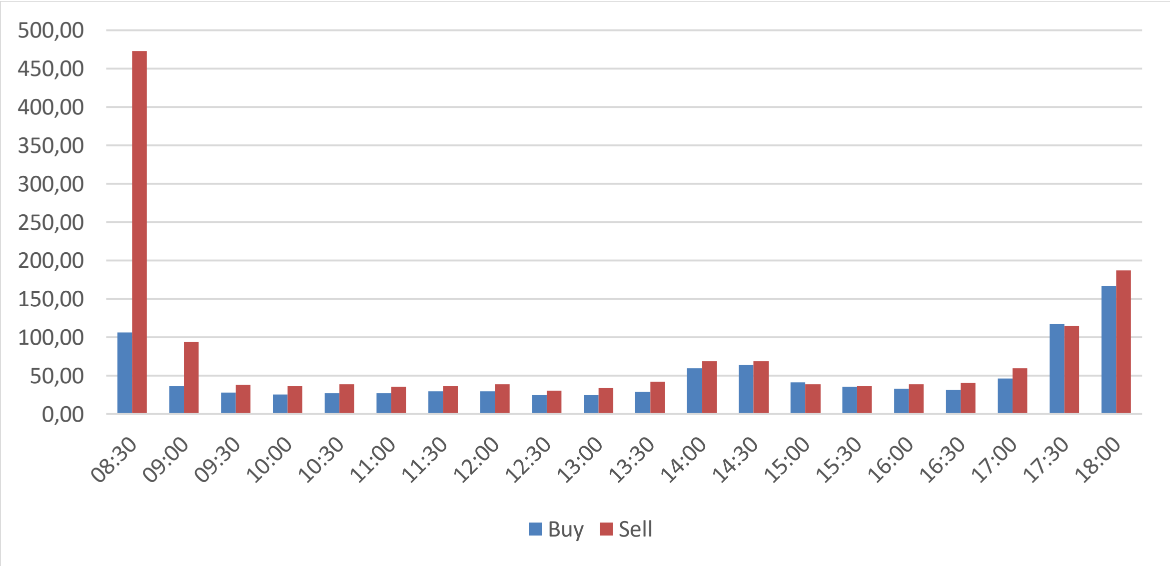
Figure 3.9: Mean volume per transaction per interval in period 1



As it can be seen in figure 3.9, the analysis of the distribution based on the mean volume per transaction does not provide such clear shape distributions as it was the case with the number of transactions and the volume of transactions. However, based on these findings some interesting facts can be noted. As in the other two variables, the distribution of the mean volume per transaction of the buy and sell credits have the same shape, with some minor differences during the dime interval of 14:00 until the interval of 14:30. The general distribution of the mean volume per transactions shows some evidences. First of all, it is clear that the credits with the highest volume for both credit transaction types are traded in the morning directly after the market opens in the interval of 08:30. The other intervals with high mean volume per transaction are the interval of 09:00, during the two intervals after the lunch time at 14:00 and 14:30 and during the last two intervals in the afternoon during the intervals of 17:30 and 18:00. As such, the distribution of the mean volume per transaction in period 1 can be characterized as a three-peak distribution. Besides these three peaks, the values remain relatively stable. In this period, the values for sell transactions are higher for almost all intervals, except the ones of 14:00 and 14:30.

The distribution of the mean volume per transaction in period 2 can be found in figure 3.10. It can be seen here that the mean volume per transaction drops in comparison to period 1. This can be regarded as a sign, that larger banks leave the market as has already been stated in different studies (e.g. Barucca and Lillo, 2018).

Figure 3.10: Mean volume per transaction per interval in period 2



Here, as in period 1, the mean volume per transaction distribution for buy and sell initiated looks almost the same during this period. After the start of the financial crisis in this period, the distribution of the mean volume holds its same shape as it was before the outbreak of the crisis. The credits with the highest mean volume per transaction can be found in the morning during the first two intervals and in the afternoon during the last two intervals. Here also, the mean volume per transaction remains quite stable during the day with an increase during the intervals of 14:00 and 14:30. In this period, the values for the sell transactions are also higher than the ones of the buy transactions, except for the intervals of 15:00 and 17:30.

The distribution of the mean volume in period 3 can be found in figure 3.11. Here it is apparent that mean volume per transaction takes smaller values indicating an even higher downgrade in the number of banks and the number banks trading credits with high values during this period.

Figure 3.11: Mean volume per transaction per interval in period 3

By taking into account the distribution in period 3, it can be seen that the distribution for sell and buy initiated transactions does not follow the same trend anymore as it was in the periods 1 and 2 when the market was still functioning well. Furthermore, the smoothness of the distributions changes. For the sell initiated credit transactions, high values can be seen at the opening of the market in the intervals of 08:30 and 09:00. The mean volume per transactions takes again high values during the intervals of 14:00 and 14:30 and again in the afternoon during the intervals of 17:30 and the interval of 18:00. In this period, there are yet again therefore distributions with three peaks: One in the morning, one after the lunch- time and one before the market closes. The mean volume per transaction for buy-initiated transactions is low as the market opens and gets higher in the interval of 09:30. High values can be seen again during the intervals of 14:00 and 14:30 and right before the market closes during the intervals of 17:30 and 18:00. Here also, the distribution can therefore be described as one with three peaks, but the sell and buy values do not follow exactly the same trend anymore. In more intervals, the buy values are also higher than the ones for sell transactions.

The distribution of the mean volume per transaction in period 4 can be found in figure 3.12. Based on this figure it can be seen that the mean volume drops even more compared to the previous periods which is again a sign for the leaving of foreign banks and the general uncertainty in the market.

Figure 3.12: Mean volume per transaction per interval in period 4

As figure 3.12 shows, the distribution of the mean volume per transaction does not look the same way for buy and sell transactions, although it still shows some interesting facts. The mean per transactions drops even more during this period, which again highlights the fact that the market becomes less system-relevant. The mean volume for sell transactions is high again in the morning during the intervals of 08:30 and 09:00 and is quite volatile during the day. Peaks again can be found after the lunch break around the intervals of 14:00 and 14:30 and in the last two intervals of the day. For the mean volume per transaction based on buy transactions I can state that it is not high when the market opens but in the second interval of 09:00. During this period, peaks for the distribution can be found before the lunchbreak in the intervals of 10:30 and 11:30 and also after the lunchbreak at the interval of 14:30. Thus, banks acting as credit borrowers in this period must search longer for credit partners for high value transactions credit lenders. The last peaks again can be also found in the last two intervals of the day at 17:30 and 18:00. During this period, I cannot state anymore that in the most intervals the values for sell transactions are higher than the ones of buy transactions.

As it can be seen, in all these mentioned distributions for the mean volume per transaction do not show such clear distributions as it was the case in the previously-mentioned variables. This analysis does, however, reveal some interesting highlights:

The general shape of the distribution can be described as a distribution with three peaks: One in the morning, one after lunch-time and one directly before the market closes. For the morning peak, I can therefore state that the adjustment of liquidity positions (Angelini, 2000), news which have been accumulated over the night (Hartmann et al., 2001) or the imbalances from transactions during the night Vento and La Ganga (2009b) are directly transferred to the liquidity management of the banks, since in the morning high value credits per transaction are been sold and bought. The high values right when the market opens and before it closes become even more noteworthy after the outbreak of the financial crisis. This means that banks buy or sell credits with high values after the outbreak of the financial crisis right when the market opens due to risk constrains and news during the day and before the market closes as there is a higher degree of uncertainty for events during the night. Finally, the high values during the first two intervals would suggest that many of these high volume credits are accounted among Italian banks, which have to be paid back until 09:00. Credit-buying banks may thus act so early in the morning in order to fulfill their credit obligation until the payback time of the credits until this time band. This would also explain the fact that there are higher values of the mean volume per transaction until this interval.

What I can also again state is, that the market participants borrow or sell credits with high values directly after lunch. Thus, there might be a tendency of the bankers to sell and buy high valued credits after the lunchtime. The high values in the afternoon again highlight the fact, that banks become active right before the market closes, as they search for other trading opportunities during the night. What is also possible is that there is here a connection between the volume of each credit and the interest rate. There might be the possibility to take up higher value credits in the morning, after lunchtime and before the market closes, to smaller credit costs meaning smaller interest rates. Here also, further analysis must be undertaken in order to test this hypothesis.

By moving away now from the general distribution and coming to the comparison of sell and buy transactions, I also find some interesting insights. For the sell transactions, the general shape of the distribution remains the same in all periods and market states. This means that based on the mean volume per transaction the banks providing credits as sellers do not change their behavior. The image is not so clear for the buy transactions: In the periods 1 and 2, the general shape remains the same, as it was for sell transactions. Afterwards in periods 3 and 4, banks take up larger credits later on the day, and not exactly after the market opens. This could again highlight the general uncertainty of the market regarding the possibility of repayment of the credit-buying banks, when the market is not functioning properly anymore. Further differences can also be found when comparing which values are higher during the day. In the first two periods, the values for sell transactions are mainly higher than the one for buy transactions. This changes when the market is no longer functioning properly. In some intervals during these periods, the sell values are higher and in some other, the buy values are higher. This again highlights the fact that when the market no longer functions properly, the transaction behavior of the banks changes. Based on these findings, I can thus state that the market becomes more volatile, highlighting on the one hand the uncertainty of liquidity for buy transactions and on the other hand, the need of banks to deposit excessive liquidity in the market for sell transactions.

When we now compare the different periods among them, I can state for periods 1 and 2 that the distributions in these periods for buy and sell transactions look almost the same and follow the same trend, with minor differences. Furthermore, we see in both periods, high values during the first two intervals in the morning and the last two intervals in the afternoon, whereas this variable stays relatively the same during the rest of the day with some increase during the intervals of 14:00 and 14:30. During these two periods, the values in the morning are higher than in the afternoon, meaning that the need for higher volume credits is higher in the morning than in the afternoon, when the market still functions properly. To sum up, for the periods 3 and 4 do not follow the same trend anymore. There are differences in the distribution of the mean volume per transactions for sell and buy initiated transactions and the smoothness of the distributions changes from period 3 to period 4, which is also a sign for the general uncertainty of the market. There are still, however, some similarities in the distributions.

3.6 Conclusion

This study presents the first analysis which takes explicitly into account the distribution of key variables on the Italian interbank credit market e-MID in the intraday frequency. That is to say, the mean number of transactions, the mean volume of transactions and the mean volume per transaction when additionally considering the differences between buy and sell credits in different market states. That means, I distinguish between buy and sell initiated credits and show the distribution of these variables during the day by analyzing the effect of the financial crisis of 2007 and onwards on these measurements.

The analyzed distributions highlight important findings: The distributions for the number of trades and the volume of trades in the different intervals can be characterized as double-humped, with high values in the morning and in the afternoon. Reasons for the hump in the morning are, e.g. liquidity shocks of the previous day and in the afternoon the closing systems and liquidity needs for the night (Cassola et al., 2010). For the distributions of the number of trades, another upward trend is found before the lunchbreak, highlighting the fact that banks become active during that time, knowing that the number of transactions is low afterwards. What is also important to take into account is that, when the market does not function properly anymore we can observe the phenomenon that more credit transactions take place earlier during the day highlighting the greater intraday uncertainty in the market. This general two-humped shape is consistent with the findings of previous studies as reported in section 3.2. This fact is interesting, due to the fact that all aforementioned studies beginning from Angelini (2000) who takes into account a data sample which spans from 01.07.1993 - 31.12.1996 until the findings of this analysis, find two-humped (or U-shaped) distributions which are still intact on the e-MID market. Thus, this is a general feature of the market.

By taking a closer look to the distributions of the number of trades, further interesting facts can be found: The distributions of the sell and buy trades have the same shape when the market is functioning properly in periods 1 and 2. This changes when the market is not functioning properly anymore in periods 3 and 4. Furthermore, the smoothness of the distributions changes, highlighting the general uncertainty of the market. This is more visible for the borrowing banks, as they are confronted with higher liquidity constraints during the day. This forces these banks to act earlier in the morning.

By taking into account the distributions of the volume of transactions, the smoothness of the distributions changes even more from period to period. This again highlights the general uncertainty of the market, even though the shape of the distributions is qualitatively the same in period 1 and 2 for buy and sell transaction but this changes again in period 3 and 4.

When comparing the values of the sell and buy transactions in both variables, number and volume of transactions during the day, it is evident that the values of the sell transactions are higher than those of the buy transactions in each interval and in each period. This is a stylized fact of the e-MID market which has been first detected in this analysis. Additionally, the gap between these two variables becomes smaller in each period. This highlights the fact that there is a shift from credit selling to even more credit buying in the e-MID market. This again also highlights the changing behavior of market participants and the general uncertainty of the market.

Based on the findings of the mean volume per transaction, I can state that in all periods the distribution shows some clear evidence for high values in the morning, as soon as the market opens and in the afternoon just before the market closes. The distributions of the sell transactions show that their shape is mainly still intact in all periods. This fact is not given for the buy transactions. During first two periods, the buy transaction distributions are qualitatively the same and in line mainly with those of the sell transactions. This changes in periods 3 and 4. Thus, based on this variable, I can state that credit selling banks did not change their behavior but buy banks did it to a great extent. The previously described stylized fact cannot be shown based on the results of the mean volume per transaction. The values of the buy transactions are higher at some intervals during the day than those for the sell transactions and in some intervals the situation is the other way around.

As already stated, there are differences between the distributions of sell and buy transactions for all variables analyzed in this paper, especially when the market is no longer functioning properly. To a large extent, this difference in sell and buy transactions is not taken into account in different papers regarding the e-MID market. The majority of studies presented, e.g. Hartmann et al. (2001) or Brunetti et al. (2010) do not take into account these differences although it is quite clear that the empirical and theoretical findings may differ when taking into account these differences. By taking into account the fact that the sell transactions are higher regarding the number and the volume of the values of buy transactions and thus the argument that the market is primarily used in order to deposit excessive liquidity, one could conclude that there might be an oversupply of interbank credits on the market. On the other hand, this oversupply may generate a lower interest rate for these credits as it may follow the basic microeconomic principle of higher supply leading to better lending conditions in terms of lower interest rates. In order to verify this hypothesis, further research is needed which puts focus on the relationship between the number and volume of transactions, the type of the transactions (buy or sell) and the intraday interest rate. This could again have an impact on the behavior of banks on the market, regarding whether they act on the market as a credit lender or credit a seller.

Unexpected events during the day may force the bank to become active during the day in the interbank credit market and to overcome liquidity shocks. In this manner, the knowledge of when the most transactions (in terms of number of trades and volume of trades) and those transactions with the highest volume per transaction take place on the market are of high interest. Such analyses become even more important when the liquidity management is distorted after the outbreak of the financial crisis and the following events, as shown in previous chapters.

Due to this kind of analysis, our understanding of the international interbank credit markets rises sharply. From a policy point of view, anomalies in the intraday dynamics indicate changes in the market states. The described differences in the buy and sell transactions should also be taken into account by further theoretical modelling as well as on different econometric time series approaches or in the analysis of the network effects of the e-MID market as well.

When comparing the findings with the other studies presented in section 3.2, I can state that the findings presented in this paper give much clearer results considering that the market functioning changes. This fact should be taken into account when analyzing the e-MID market in the intraday frequency. When comparing my findings based on the mean number of transactions and the mean volume per interval with the findings of previous studies, I can state that these are in line in the periods 1 and 2, when the market functions properly. This changes when the market is not functioning anymore in periods 3 and 4, as the smoothness of the distributions change. Hence, for the analysis of the interbank credit market, different market states and the differentiation of sell and buy transactions should be taken into account. By comparing my findings based on the mean volume per transaction with the previous studies, I can state that the results may be in line again when the market functions well, but do change when this is not given anymore. This analysis represents the first study to show these changing intraday distributions on the e-MID market. The findings based on the mean volume per transaction could play an important role for the liquidity management of banks, since they can now optimize their trading strategies when it comes to the selling and buying of credits with high values. Furthermore, these findings could be used for further econometrical or empirical analyses, as e.g. for the implementation of further network formations on the e-MID market.

By taking into account the comparison with other segments of the financial markets, my results show that there are similarities in these distributions. The question which arises is whether a previous / later trading in these segments of the financial markets may affect the behavior of the trading in the e-MID market. This could also be an explanation for the different distributions on the e-MID market.[47]

What is furthermore interesting to analyze in the near future is the volume distribution by comparing different types of aggressors and quoters based on the country of origin. The mean volume per transaction for credits between Italian banks in my data sample equals 22.54 million euro. On the other hand, when a foreign bank is involved in the credit transaction, the mean volume per transaction is more than four times higher than between Italian banks, at 98.64 million euro. By looking at this measurement for credit transactions only between foreign banks, calculations show that the mean per transaction is 263.99 million euro, which is approximately ten times higher than the mean of the credit volume between Italian banks. Therefore, from my point of view, further research should be aimed at the different countries of origin and based on my findings in this paper by also taking into account the intraday distribution and the different market states.

Furthermore, I suggest analyzing the market based also not only on daily data, but also on a lower frequency, e.g. on a monthly or yearly basis.[48] Based again on calculations it can be shown that there are differences between the monthly values of the number and the volume of transactions. Therefore, it would be useful, from a theoretical but also from a practical point of view, if further research would consider patterns of monthly effects in the market, which could influence the behavior of the banks in the market. In addition, different market states might be again distinguished. Results obtained by moving away from the intraday domain would be also interesting from a theoretical point of view, as these credits with higher maturities are not being traded due to short liquidity constraints but due to other reason, e.g. for longer term investments. It was one of the aims of this paper to establish an empirical starting point for these kinds of research.

[47] This aspect will be left for further research as it would go beyond the scope of this analysis.

[48] Only few studies focus on the lower frequency in the e-MID market. Hartmann et al. (2001) and Barucca and Lillo (2018) focus on weekly data, Angelini et al. (2009) focus on interbank transactions with a maturity of one week until 12 months and Hartmann et al. (2001), Temizsoy et al. (2015) and Gabbi et al. (2012) focus on monthly data.

V. References

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