

Liquidity Provision in the Interbank Foreign Exchange Market

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LIQUIDITY PROVISION IN THE INTERBANK FOREIGN EXCHANGE MARKET

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During my PhD, I experienced how intimidating a blank sheet of paper can be. It confronts you with questions such as “Where to start?”, but also “Where did it all start?”. The second question can be even more difficult to answer than the first. In any case, the decision to enroll for a PhD program in economics/ finance in 2008, right after my master studies, came at a time when there were many things I wanted to understand. In those days, financial markets were in the center of the attention of society. The markets were constantly in the headlines of the news, and they were apparently dictating the decisions of world leaders. Although their importance was obvious, their functioning remained to a large extent a mystery to me: it was a world of complex products, populated by actors who all claim to be rational and who follow sophisticated strategies. In those days, I met my advisor, Prof. Dr. Michael Frömmel, who was teaching a course on Investment Analysis. His course made me even more interested in the topic, and by the time the course was over, I had even more questions than before I started it (they became more advanced, though). It was Michael who took the initiative, and who offered me a platform to focus on the questions I had. Already very early, he introduced me to market microstructure. Immediately after this introduction, the working title of my PhD became “Essays in Market Microstructure”. I am very grateful to Michael that he offered me the opportunity to do a PhD in the first place, and that he directed me towards this exciting field. He gave me already from the very beginning the opportunity to develop a wide range of skills, and allowed me to broaden my horizons in many different ways. As advisor, he was willing to consider all suggestions and ideas I came up with, and we had many open discussions. Furthermore, he always had some words of encouragement (and these words were from time to time very welcome), and he – crucially – always supported me.

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¹ Schumpeter, Joseph, 1942, *Capitalism, Socialism and Democracy*, New York: Harper.

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Overview of the dissertation

Market liquidity captures how easy it is to convert an asset into cash and is a key-variable of interest when trading on financial markets and when investigating them. Moreover, liquidity also determines the speed at which information about an asset can be processed and it affects as well the asset's expected return. From a policy perspective, liquidity is an important factor for the stability of the global financial system. In this thesis, we study market liquidity by looking at the interaction amongst different types of participants on the Hungarian forint/ euro interbank foreign exchange market.

In the **first chapter** we start from a very general level – in an international finance framework – by surveying the literature on exchange rate policy in Central and Eastern European Countries (CEEC's). In 2004, a first wave of CEEC's joined the European Union. As a result, these countries all have the common long-term goal of joining European Monetary Union. Joining the monetary union is, however, conditional on the realization of the Maastricht criteria, and these criteria include stability of the exchange rate inside the European Exchange Rate Mechanism (ERM II). Despite their common goal, the CEEC's opted for different exchange rate policies. Furthermore, their exchange rate policies were subject to frequent changes and adjustments. In this chapter, we describe the official exchange rate arrangements in the CEEC's, but we also consider the difference between de jure and de facto exchange rate regimes. Next, we survey the literature on exchange rate volatility and the link with exchange rate policy and monetary policy. Therefore, we consider switches between volatility regimes. A big difference between the timing of these switches and the dates of the respective policy changes may hint at a lack of credibility of the policy, including the unpeaceful exits from the pegs in the Czech Republic and Slovakia. Finally, we survey the literature on the influence of monetary authorities on the exchange rate. Here we look, amongst other things, to central bank intervention and central bank communication in CEEC's.

From the next chapter onwards we switch on the microscope, and look at the market microstructure of the interbank foreign exchange market. Throughout these chapters we use detailed data for the Hungarian forint/ euro market – which operates as an electronic limit order book – in 2003 and 2004. In the **second chapter** we investigate the link between news announcements, jumps (which are basically price discontinuities) and market liquidity. In a first stage we detect the intraday jumps, and show that they are prevalent and important: there

is at least one price jump on 18.20% of the trading days contained in our sample period, and 42.59% of the price variation on these jump days can be attributed to the jumps. We also find that positive and negative jumps are symmetric in terms of both frequency and size.

In a second stage, we try to link the intraday jumps with public news announcements. Here we consider both scheduled public news (e.g. GDP, PPI, trade balance information,...) and unscheduled public news (e.g. central bank interventions, polls, surveys, political changes,...). They can be respectively linked with 16% of the jumps and 30.4% of the jumps, which implies that more than half of the jumps cannot be explained by public information.

Hence, we would like to take a closer look at the actual genesis of jumps: are they caused by (public or private) information inflow, noise trades or insufficient liquidity? We therefore study in a third stage the dynamics of liquidity in a two-hour window around the jumps. We look at liquidity as a multi-dimensional variable and distinguish the tightness dimension (the difference between the best bid and the best ask), the immediacy dimension (the amount of euro or forint traded), resiliency (the pace at which the price reverts to former levels after it changed in response to large order flow imbalances), the overall depth (the amount of euro or forint available in the limit order book) and the depth at the best quotes. As a result, we find that jumps do not happen when liquidity is unusually low, but rather when there is an unusually high demand for immediacy concentrated on one side of the order book. Moreover, this result is independent of whether the jump can be linked to a public news announcement or not, and our findings suggest that it is information inflow that causes the jump. Moreover, a dynamic order placement process emerges after a jump: more limit sell (buy) orders are added to the book subsequent to a positive (negative) jump. We attribute this to endogenous liquidity providers on the market. Attracted by the higher reward for providing liquidity, they submit limit orders at the side where it is needed the most.

In a fourth and last stage, we provide some further analyses and apply a probit model that shows that none of the liquidity variables offers predictive power for a jump occurrence (consistent with what we find for the dynamics of liquidity around jumps) or for the magnitude of the jump. In addition, we find that more limit orders relative to market orders are submitted to the book after the jump, and that the post-jump order flow is in general less informative than in normal trading periods. Overall, our results provide insight into the origin of jumps and map the impact of endogenous liquidity provision on this market without designated market makers.

In the last two chapters, we zoom in on the process of endogenous liquidity provision. We focus in these chapters on the link between the tightness dimension/ bid-ask spread and the cost of providing liquidity. We distinguish respectively order processing costs (the operational costs of providing market making services, such as wages of traders, floor space rent, fees that have to be paid to the platforms,...), inventory holding costs (the cost of holding an unwanted inventory, which results from accommodating incoming orders) and adverse selection costs (the cost of engaging in a transaction with a market participant who has superior information). In the **third chapter** we provide evidence using an established, structural model that allows us to split up the spread into these different cost components. We find that over the two years, 40.09% of the bid-ask spread can be explained by inventory holding costs, 38.34% can be explained by order processing costs and 21.57% can be explained by adverse selection costs. Our results differ in some ways from previous results for the foreign exchange market where the same methodology was used, and are to some extent more intuitive. In comparison with the existing studies, the tier of the market we analyze, the completeness of the data, the size of the market and institutional differences between markets seem to play an important role. Furthermore, we find that the estimated spread on large trades is over the whole dataset 32.35% higher than the spread on small trades. We show that this higher spread is caused by a higher combined inventory holding and adverse selection cost.

In the **fourth chapter**, we follow a novel direction. Here we study the bid-ask spreads using an empirical spread decomposition model and specify the individual spread components explicitly. The combined inventory holding and adverse selection cost is here modeled as an option premium. This is very intuitive, and has the advantage that the risk can be quantified using option valuation techniques. We provide the first complete forex results for this type of model, and show that the combined component accounts for 52.52% of the bid-ask spread. Furthermore, we provide evidence for an endogenous tick size of 0.05 HUF/ EUR and we also estimate the number of liquidity providers based on the results for the risk component.

In addition, the empirical approach we follow in this chapter allows us to examine two interesting spread patterns: the stylized difference in spreads between peak-times and non-peak times and the spread pattern around a speculative attack against the Hungarian forint in the beginning of 2003. First, we confirm the stylized difference in spreads between peak-times and non-peak times. As a matter of fact, during non-peak times the spread is more than double as high as during peak-times. We find that this is caused by an increase in the risk component, and if we elaborate on the origin of it we show that it is not only the calculated

option premium that increases but also the sensitivity to this option premium. Clearly, the increase in the premium still underestimates the actual increase in risk for the liquidity provider. We explain this by the increased probability that the liquidity provider will have to keep his position overnight.

Second, we map the spread pattern around the speculative attack. Prior to the attack, the spread decreases until it reaches a level below the endogenous tick size. This decrease is caused by a strong decrease in the risk component. During the speculative attack, the spread increases massively, as a result of the rising risk component. The order processing component, on the other hand, decreases at the same time. This pattern is consistent with increased competition amongst liquidity providers who are well aware of the increased risk that their activity during this period of high speculation involves. After the attack, both the order processing component and risk component increase. Consequently, the tightness of this market is much lower than before the attack. Overall, this chapter demonstrates the relevance of an option based decomposition approach for understanding how liquidity is provided on the interbank foreign exchange market.

Samenvatting van het proefschrift

Marktliquiditeit omvat hoe makkelijk het is om een investering in een financieel actief om te zetten in contanten en is van essentieel belang wanneer men handelt op financiële markten of wanneer men deze markten onderzoekt. Overigens bepaalt de liquiditeit van een actief eveneens de snelheid waarmee informatie kan worden geïncorporeerd in de prijs, en beïnvloedt zij ook de verwachte opbrengst van het actief. Vanuit het standpunt van een beleidsmaker is liquiditeit belangrijk voor de stabiliteit van het globale financiële systeem. In dit proefschrift bestuderen wij marktliquiditeit door de interactie tussen verschillende types actoren in de handel op de Hongaarse forint/ euro wisselmarkt voor banken in kaart te brengen.

In het **eerste hoofdstuk** vertrekken we heel algemeen vanuit het denkkader van de internationale financiën. We geven een overzicht van de bestaande wetenschappelijke literatuur over wisselkoersbeleid in de landen uit Centraal- en Oost-Europa (hierna CEEC's genoemd). In 2004 is een eerste groep CEEC's toegetreden tot de Europese Unie. Bijgevolg hebben al deze landen het gemeenschappelijke doel om finaal toe te treden tot de Europese Monetaire Unie (EMU). Toetreden tot de EMU is echter slechts mogelijk mits naleving van de Maastricht criteria, die onder andere stabiliteit van de wisselkoers binnen het Europese Wisselkoersmechanisme (ERM II) omvatten. Niettegenstaande hun gemeenschappelijke doel, hebben de CEEC's geopteerd voor verschillende types van wisselkoersbeleid. Verder is hun wisselkoersbeleid regelmatig gewijzigd. In dit hoofdstuk beschrijven we in eerste instantie het officiële wisselkoersbeleid van de verschillende CEEC's, maar houden we eveneens rekening met het verschil tussen "de jure" en "de facto" wisselkoersbeleid. Vervolgens geven we een overzicht van de wetenschappelijke literatuur omtrent de volatiliteit van de wisselkoers, en het verband met wisselkoersbeleid en monetair beleid. We focussen hierbij vooral op veranderingen tussen volatiliteitsregimes. Zij kunnen ons – in combinatie met gegevens over het beleid – een indicatie geven van de geloofwaardigheid van het beleid: indien veranderingen in de volatiliteitsregimes en veranderingen in het beleid op verschillende momenten plaatsvinden, duidt dit op een gebrek aan geloofwaardigheid van het beleid. Dit was bijvoorbeeld het geval toen Tsjechië en Slowakije hun vaste wisselkoers ongepland verlieten. We sluiten dit hoofdstuk af met een overzicht van de wetenschappelijke literatuur over de invloed van monetaire beleidsmakers op de wisselkoers. Hier beschouwen we, onder

andere, interventies van centrale banken en communicatie door centrale banken in de CEEC's.

In de rest van het proefschrift zetten we de microscoop aan, en concentreren we ons op de microstructuur van de handel op de wisselmarkt voor banken. Over de verschillende hoofdstukken heen gebruiken we hier gedetailleerde data van de Hongaarse forint/ euro markt – die functioneert aan de hand van een limiet orderboek – in 2003 en 2004. In het **tweede hoofdstuk** onderzoeken we het verband tussen aankondigingen van nieuws, jumps (die in essentie discontinuïteiten zijn in de prijs) en marktliquiditeit. In eerste instantie sporen we daartoe jumps gedurende de dag op, en tonen we aan dat zij vaak voorkomen en belangrijk zijn: er is ten minste één jump gedurende de dag op 18,20% van de handelsdagen die onze dataset bevat, en 42,59% van de prijsvariatie op deze dagen kan toegewezen worden aan de jumps. We vinden verder ook dat positieve en negatieve jumps symmetrisch zijn in termen van frequentie en grootte.

In tweede instantie gaan we jumps gedurende de dag in verband brengen met aankondigingen van nieuws. We beschouwen hier zowel geplande publieke aankondigingen (zoals bijvoorbeeld BBP, index van de producentenprijzen, handelsbalansinformatie,...) als ongeplande publieke aankondigingen (zoals bijvoorbeeld interventies door de centrale bank, bevragingen, politieke veranderingen,...). Zij kunnen respectievelijk in verband worden gebracht met 16% van de jumps en 30,4% van de jumps, wat impliceert dat meer dan de helft van de jumps niet kunnen worden verklaard door publieke informatie.

We zouden dan ook meer inzicht willen verkrijgen in de genese van jumps: worden zij veroorzaakt door een instroom van publiek of privaat nieuws, noise handel of onvoldoende liquiditeit? Om hierop een antwoord te krijgen, gaan we in derde instantie de liquiditeitsdynamiek bestuderen in de twee uren rond jumps. We beschouwen liquiditeit hier als een variabele die meerdere dimensies heeft, en onderscheiden de strakheid (het verschil tussen de beste biedprijs en de beste laatprijs), de directheid (de hoeveelheid euro of forint die verhandeld wordt), veerkracht (de snelheid waarmee een prijs zich terug herstelt naar een eerder niveau, nadat hij gewijzigd is door een groot onevenwicht in de orderstroom), de diepte van het orderboek (de hoeveelheid euro of forint die beschikbaar is in het orderboek) en de diepte tegen de beste prijs. Onze analyse toont dat jumps niet gebeuren op een moment dat de liquiditeit ongewoon laag is, maar eerder wanneer er een ongewoon hoge vraag naar directheid is die geconcentreerd is op één zijde van het limiet orderboek. Dit resultaat geldt overigens zowel voor jumps die in verband kunnen worden gebracht met de aankondiging van nieuws, als voor jumps voor dewelke dit niet het geval is, en onze resultaten suggereren dat

het een instroom van informatie is die de jump veroorzaakt. Verder zien we dat door de jump een dynamisch proces ontstaat waarbij limiet verkooporders worden geplaatst na een positieve jump en limiet kooporders na een negatieve jump. We schrijven dit toe aan endogene liquiditeitsvoorzieners op deze markt. Aangetrokken door de hogere compensatie voor het voorzien van liquiditeit op de markt, voegen zij limiet orders toe aan de zijde van het orderboek waar dit het meest nodig is.

In vierde instantie voeren we enkele verdere analyses uit en passen we een probit model toe dat aantoont dat geen enkele van de dimensies van liquiditeit in staat is om een nakende jump te voorspellen (in overeenstemming met wat we vonden in de sectie over de liquiditeitsdynamiek rond jumps) of de grootte ervan. Verder vinden we ook dat het relatief aandeel van limietorders ten opzichte van marktorders toeneemt na een jump, en dat de orderstroom na de jump minder informatie bevat dan onder normale omstandigheden. Globaal genomen verschaffen onze resultaten inzicht in de oorsprong van jumps, en brengen zij de impact van endogene liquiditeitsverschaffers in kaart op deze markt waar geen speciale marketmakers zijn aangesteld.

In de laatste twee hoofdstukken wordt er ingezoomd op het proces waarbij liquiditeit op een endogene manier wordt aangeboden. We focussen hierbij op de link tussen de strakheid van de markt/ het verschil tussen de bied- en laatprijs (hierna de spread genoemd) en de kostprijs van het aanbieden van liquiditeit. We onderscheiden respectievelijk order verwerkingskosten (hierna OPC genoemd, de operationele kosten van het aanbieden van liquiditeit, zoals de lonen van handelaren, de huur van de kantoren, honoraria die dienen te worden betaald,...), voorraadkosten (hierna IHC genoemd, de kostprijs van het aanhouden van een ongewenste voorraad) en averechtse selectiekosten (hierna ASC genoemd, de kostprijs van het handelen met partijen die over meer en/ of betere informatie beschikken dan de aanbieder van liquiditeit). In het **derde hoofdstuk** leveren we resultaten met behulp van een gevestigd structureel model dat ons toelaat de spread op te splitsen in de verschillende kostencategorieën die we hierboven introduceerden. We tonen aan dat over de periode van twee jaar, 40,09% van de spread verklaard kan worden door IHC, 38,34% kan verklaard worden door OPC en 21,57% kan verklaard worden door ASC. Onze resultaten verschillen op sommige vlakken van bestaande resultaten voor de wisselmarkt voor dewelke dezelfde methodologie werd gebruikt. Ze zijn tot op zekere hoogte ook meer intuïtief. In vergelijking met bestaande studies spelen de aard van de markt die wij beschouwen, de volledigheid van onze data, de grootte van de markt en institutionele verschillen een belangrijke rol. Verder vinden we dat de geschatte spread die aangerekend wordt bij grotere verhandelde volumes

32,35% hoger ligt dan de spread die aangerekend wordt bij kleinere verhandelde volumes. We tonen dat de hogere spread in dat geval wordt veroorzaakt door een hogere gecombineerde IHC en ASC.

In het **vierde hoofdstuk** volgen we een nieuwe richting binnen het onderzoek naar de microstructuur van financiële markten. Dit houdt in dat we de spreads bestuderen aan de hand van een empirisch model dat ons toelaat de spread op te splitsen in de verschillende kostencategorieën. Daarbij wordt elke kost expliciet gespecificeerd en gekwantificeerd, en hier wordt de som van de IHC en de ASC gemodelleerd als een optiepremie. Dit is heel intuïtief, en heeft als voordeel dat het risico kan worden gekwantificeerd aan de hand van technieken voor optiewaardering. We leveren de eerste volledige resultaten voor de wisselmarkt voor dit type model, en we tonen dat de gecombineerde risicocomponent instaat voor 52,52% van de spread. Verder vinden we bewijs voor een endogene minimale prijsverandering van 0,05 HUF/ EUR en schatten we het aantal verschaffers van liquiditeit op basis van de resultaten voor de risicocomponent.

Aansluitend laat het empirische model dat we in dit hoofdstuk hanteren toe om twee interessante patronen in de spread te bestuderen: het vaste verschil in spread tussen piekuren en daluren, en het patroon van de spread rond een speculatieve aanval tegen de forint in het begin van 2003. We tonen eerst aan dat de spread tijdens de daluren meer dan dubbel zo hoog is als tijdens piekuren. Dit is te wijten aan een toename van de risicocomponent, en als we verder ingaan op de oorzaak van deze toename zien we dat niet enkel de optiepremie toeneemt, maar ook de gevoeligheid voor deze optiepremie. We leiden hieruit af dat de berekende optiepremie het risico voor de verschaffer van liquiditeit nog onderschat. Dit is het gevolg van het risico dat hij zijn positie zal moeten aanhouden gedurende de nacht.

Daarna brengen we het patroon van de spread rond de speculatieve aanval in kaart. Vóór de aanval daalt de spread tot hij een niveau bereikt dat onder de endogene minimale prijsverandering ligt. Deze daling wordt veroorzaakt door een sterke daling in de risicocomponent. Tijdens de aanval neemt de totale spread toe door een sterke stijging van de risicocomponent. De OPC dalen tijdens de aanval. Dit patroon kan verklaard worden door hogere competitiviteit tussen verschaffers van liquiditeit, die zich tegelijkertijd heel bewust zijn van het risico dat zij nemen door liquiditeit te verschaffen in een periode van hoge speculatie. Na de aanval nemen zowel de OPC als de risicocomponent toe. Bijgevolg is de strakheid van de markt veel lager dan voor de aanval. Globaal genomen toont dit hoofdstuk de relevantie aan van een model om de spread op te splitsen aan de hand van opties om te begrijpen hoe liquiditeit wordt verschaft op de wisselmarkt voor banken.

Chapter 1

**Exchange Rate Policy in Central and
Eastern European Countries**

Exchange Rate Policy in Central and Eastern European Countries*

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Abstract

The Central and Eastern European Countries (CEEC's) which joined the European Union between 2004 and 2007 show an interesting evolution of their exchange rate regimes. Although they all started from a comparable situation and have the common long-term goal of joining European Monetary Union, they opted for different exchange rate policies. Furthermore, the exchange rate policies were subject to frequent changes and adjustments. We first describe the evolution of exchange rate arrangements in CEEC's, and survey in this paper various aspects of their exchange rate policy.

We start with the discussion of differences between de facto and de jure exchange rate regimes. Second, we analyze the impact of exchange rate policy on exchange rate volatility, focusing on structural breaks or volatility regimes. While the level of volatility shows the external dimension of monetary stability, the break points may help to understand the processes that lead to changes in exchange rate arrangements. Third, we highlight the role of CEEC's exchange rates in monetary policy rules. Finally we review the literature on central bank interventions in CEEC's.

JEL: E58, F3

Keywords: European Union, Central and Eastern European Countries, transition economies, exchange rate policy

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Exchange Rate Policy in Central- and Eastern European Countries

1. Introduction

The European Union has grown substantially in the 21st century. The first wave of Central and Eastern European Countries (CEEC's) joined in 2004, namely the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovenia and Slovakia (plus Cyprus and Malta), while Bulgaria and Romania followed in 2007. All countries have the obligation to join European Monetary Union. This is, however, conditional on the realization of the Maastricht criteria. Since these criteria include stability of the exchange rate inside the European Exchange Rate Mechanism (ERM II) for two years, the exchange rate policy of the CEEC's is of major importance and the question arises which is the 'best' exchange rate arrangement for CEEC's. The CEEC's show an interesting evolution of their exchange rate regimes. Although they all started from a comparable situation and have the common long-term goal of joining European Monetary Union, they opted for different exchange rate policies. Furthermore, the exchange rate policies were subject to frequent changes and adjustments. We first describe the evolution of exchange rate arrangements in CEEC's, and survey in this paper various aspects of their exchange rate policy. Since there has been a plethora of works on exchange rates in CEEC's, the survey has to be both, subjective and selective. We are aware of the fact that this approach is incomplete and the survey is not intended to be exhaustive.

A natural starting point is the description of the evolution of (official) exchange rate arrangements in the CEEC's in section 2. However, it is known that what countries announce to be their exchange rate regime and what they de facto implement often differs. For this reason we review the literature on differences between de facto and de jure exchange rate regimes.

In section 3 we analyze the relation of exchange rate policy and exchange rate volatility. Since the CEEC's frequently modified their exchange rate arrangements, there has been a strong focus on structural breaks or volatility regimes. Since the level of volatility is often understood as external dimension of monetary stability, one should expect a close relation between monetary policy regimes and exchange rate volatility. At the same time, switches between volatility regimes that deviate from the dates of the respective policy changes may hint at a lack of credibility of policy, including the unpeaceful exits from the pegs in the Czech Republic and Slovakia.

The last sections deal with the influence of monetary authorities on the exchange rate. We start in section 4 with the role of the exchange rate in monetary policy rules. In contrast, section 5 reviews the literature on central bank interventions in CEEC's, including central bank communication.

2. Evolution of exchange rate regimes

The exchange rate regimes in Central and Eastern European countries underwent a remarkable evolution in the past two decades. This evolution is illustrated in Figure 1. We see that most of the CEEC's chose a fixed exchange rate¹ as a tool in their stabilization strategy after the dissolution of the Soviet Union in December 1991. The standard arguments behind the fixed exchange rate are the reduction of transaction costs for external trade and macroeconomic stabilization (Halpern & Wyplosz 1997). Additionally, at least two major reasons can be given for why countries may not let their currency float freely.² First, small open economies are highly susceptible to exchange rate movements; therefore, the exchange rate must be considered by monetary authorities even if it is not the primary goal of monetary policy (Ball 1999). Most of the EU accession countries in Central and Eastern Europe belong to this class of countries. Second, in many emerging and transition countries, financial markets are less developed and do not allow domestic firms to borrow in their home currency. This is considered to be the original sin (Eichengreen & Hausmann 1999). Because their debt is nominated in foreign currency they will have incentives to peg their exchange rates because their debt is nominated in foreign currency, as (Hausmann *et al.* 2001) argue.

Even after considering the above mentioned arguments, a country may still not find it convenient to commit to an official peg. The political support for the necessary but unpopular measures to defend the peg may be very low in emerging and transition countries (Obstfeld & Rogoff 1995). Furthermore, under an officially floating regime, adjustments of the exchange rate are less visible to the public and less costly politically than devaluations under an official peg (Obstfeld 1997).

[Insert here: Figure 1: Exchange rate regimes in CEEC's]

¹ A fixed exchange rate is sometimes referred to as a pegged exchange rate.

² The literature on optimum currency areas surveyed by (De Grauwe 2003) suggests that the choice of a pegged exchange rate is feasible only for a limited number of countries.

We see in Figure 1 that in the late 1990s, many countries moved to more flexible arrangements (Sachs 1996). The Visegrád Group, i.e., the Czech Republic, Hungary, Poland and Slovakia followed entirely this path (Kocenda 2002). The combined strategy of a fixed exchange rate directly after the transition and a more flexible regime later on adds the benefits from pegging to the anchor currency to the ability to cope better with volatile capital movements in the later period (Corker *et al.* 2000).

The Czech Republic and Slovakia opted initially for narrow horizontal bands. Subsequently, these fixed exchange rate regimes became more flexible and, after widening the bands, the Czech Republic (1997) and Slovakia (1998) declared managed floating or freely floating exchange rates.

Poland and Hungary chose narrow crawling bands that served the dual objectives of maintaining competitiveness and moderating inflation (Szapáry & Jakab 1998). In 2000 the Polish zloty was declared freely floating. In Hungary the band was widened in 2001 to 15% and changed from a crawling to a horizontal band to mirror the exchange rate regime envisaged in the Exchange Rate Mechanism (ERM-2). Hungary kept a fixed exchange rate until early 2008. Early in the transition, other countries opted either for completely fixed exchange rates, e.g., the Baltic States and Bulgaria, or rather flexible regimes, e.g., Romania and Slovenia.³ The Baltic States all stepped in the ERM system. Still, they chose to keep their currencies *de facto* fixed. The reported bandwidth of 15% remains thus purely theoretical. Estonia is announced to join the Eurozone on the first of January 2011.

The development described above follows the so called bipolar view.⁴ The bipolar view is based on the idea that, in a world of high capital mobility, adjustable pegs may be costly and difficult to defend so that they will be replaced by either hard pegs, i.e. currency boards and currency unions, or absolutely flexible exchange rate systems. The bipolar view is currently a mainstream conclusion in exchange rate policy. According to the official classification by the International Monetary Fund (IMF), the share of intermediate exchange rate regimes has declined during the last decade, as (Fischer 2001) discusses. This confirms the bipolar view.

3. De jure versus de facto exchange rate regimes

In the previous paragraph we gave an overview of the “*de jure*” exchange rate regimes of the CEEC’s, or in other words “what countries say they are doing”. Still, this may not be what

³ Exchange rate arrangements chosen by transition countries are discussed in (Mussa *et al.* 2000)

⁴ The bipolar view is also named as the hollowing out hypothesis or the two-corner hypothesis

countries are actually doing. In practice fear of floating and de facto pegging is very common (Calvo & Reinhart 2002).⁵ Hence, the IMF acknowledges since 1999 de facto exchange rate regimes. The IMF classification remains a hybrid system: it combines data on actual flexibility with information on the official policy framework (IMF, 2004). According to the hybrid classification, the Slovenian and Romanian exchange rate regimes are crawling pegs, whereas these two countries announced to be managed floats. Relying solely on the official announcements could be misleading, especially for economies in transition. Knowing whether countries follow their officially announced exchange rate is crucial for assessing economic performance in terms of growth, volatility, inflation, and sensitivity to crises, as (Reinhart & Rogoff 2004) discuss. In the literature most studies are based on de jure classifications until the late 1990s. Recent literature, e.g. (Flood & Rose 2005), tries to classify exchange rate arrangements in a more realistic manner.

In general, two main approaches can be followed to identify de facto exchange rate regimes. One approach analyzes the development of exchange rates and policy variables that are indicative of exchange rate management by the central bank. (Popper & Lowell 1994) take this approach for Pacific Basin countries; (Hausmann *et al.* 2001) and (Levy-Yeyati & Sturzenegger 2005) use it on a broad sample of countries. (Schnabl 2004) applies this technique to the CEEC's. The second approach considers the outcomes of implicit exchange rate targeting, i.e., the time series of exchange rates. This can be done by comparing exchange rate developments with those of some possible anchor currencies. Exemplary for this approach is the work of (Haldane & Hall 1991). They analyze the transition of the British Pound from a dollar peg to a Deutsche mark peg. Other examples include (Frankel & Wei 1992), who investigate the influence of the yen on the exchange rate policies of some Asian countries and (Frankel *et al.* 2001), who consider its impact on other emerging market economies. Some CEEC's have been included in the work of (Bénassy-Quéré 1996), who investigates de facto pegs during their early period of transition. (Reinhart & Rogoff 2004) stress the importance of market-determined exchange rates and also consider the behavior of parallel exchange rates to construct a natural classification algorithm.

(Frömmel & Schobert 2006) use the approach by (Frankel & Wei 1992) to analyze the de facto exchange rate regimes of six CEEC's, namely the Czech Republic, Hungary, Poland,

⁵ (Fischer 2001), (Reinhart & Rogoff 2004), (Levy-Yeyati & Sturzenegger 2005), and (McKinnon & Schnabl 2004) also support this view. (Rogoff *et al.* 2004) state that, from an ex post perspective, the de facto exchange rate regime differs from the announced one about 50% of time.

Romania, Slovakia and Slovenia. They use daily data from 1994 to 2004, when most of the countries under consideration joined the European Union and estimate the regression:

$$\Delta s_t = d + \sum_{i=1}^N w_i \cdot \Delta s_{i,t} + \varepsilon_t \quad (3.1)$$

where s_t is the currency under observation expressed in special drawing rights that are used here as a numeraire, d is the rate of crawl, t the time parameter and $s_{i,t}$ are currencies to which s_t is pegged.

The currencies $s_{i,t}$ are expressed in the same numeraire as s_t and weighted in the basket with some weights w_i , which are nonnegative real numbers. The specification of equation (1) nests several relevant alternative regimes. A simple peg implies $d=0$ and $N=1$, while a crawling peg indicates $d>0$ and $N=1$. A basket peg results in $d=0$ and $N>1$, while a crawling basket implies $d>0$ and $N>1$.

The setting of eq. (3.1) allows testing the de facto exchange rate regime. First one may test whether the rate of crawl (d) or the estimated weights (w_i) are different from zero. Second it is possible to test whether the estimated weights significantly differ from the officially announced ones.

Their findings imply that the Polish zloty and the Hungarian forint have most likely behaved according to their officially announced regime during their periods of higher exchange rate flexibility, while the results for the Czech Republic and Slovakia suggest a somewhat higher importance of the euro (and Deutsche mark) than officially announced. The Slovenian regime before 2004 matches rather the IMF's de facto classification as a crawling peg than its official announcement of a managed float. Although (Frömmel & Schobert 2006) cannot clearly confirm the Romanian regime as a de facto crawling peg, it occasionally seemed like a crawling peg to a basket of euro and US dollar.

4. Exchange rate regimes and volatility

As pointed out above, we observe an increasing degree of exchange rate flexibility for the CEEC's between 1994 and 2004.⁶ This increased flexibility of the exchange rate, however,

⁶ This movement towards more flexible exchange rate arrangements stopped in recent years after several of the CEEC's joined the exchange rate mechanism (ERM2) of the European Monetary System and pegged their exchange rate to the euro within a band of ± 15 percent. This is the case in particular for Slovakia and Slovenia, which had officially announced managed floats prior to their entry to ERM2. Slovenia and Slovakia joined EMU in 2007 and 2009, respectively.

may not necessarily lead to higher volatility. In support of this, (Krugman 1991) argues that widening the fluctuation band will make it more credible, because it gets less likely that the fluctuation margins will be reached. Consequently volatility decreases. In contrast, (Flood & Rose 1999) conclude that fixed exchange rate regimes are in general less volatile than floats. This was also found by (Hughes-Hallett & Anthony 1997) and (Frömmel & Menkhoff 2001) for the European Monetary System. (Stancík 2007) corroborates this result for the Visegrád countries and Slovenia, but also stresses the importance of trade openness. (Frömmel & Menkhoff 2003) additionally show that changes in monetary policy settings determine volatility switches for exchange rates of major industrial countries.

Some empirical results suggest that the effect on volatility of the type of exchange rate regime is conditional on the appropriateness of the exchange rate regime. The work of (Berger *et al.* 2000) confirms that the type of exchange rate regime affects volatility, but that the “wrong” choice of a peg (that is, the choice of a peg by a country for which a flexible exchange rate would be more appropriate) induces higher exchange rate volatility than a peg which is in line with the macroeconomic conditions. Accordingly, volatility can here be seen as a measure of credibility of an exchange rate arrangement and serves as “a symbolic and visible measure of the government’s success in macroeconomic management” (Duttagupta *et al.* 2004). (Fidrmuc & Horváth 2008) apply various GARCH-type models to five new member states of the EU and find an inverse relation between credibility of the exchange rate regime and exchange rate volatility.

There are only few works which investigate structural breaks in the exchange rate volatility of Central and Eastern European transition economies. (Kocenda 1998) compares GARCH estimates for the Czech koruna before and after the exchange rate band was widened in 1996 and finds significantly differing volatility patterns. (Kóbor & Székely 2004) apply a simple Markov switching model to the exchange rates of the so called Visegrád Group (the Czech Republic, Hungary, Poland, and Slovakia) between 2001 and 2003 and find frequent regime switches. Their sample period however does not include any change of the officially announced exchange rate system. (Kocenda 2005) argues that a lack of coincidence between policy changes and structural breaks in exchange rate behavior may hint at policy settings which are not consistent with the opinion of market participants and, accordingly, low credibility of the system. This is in line with the observation that if the costs of changing an exchange rate regime are high, a country may uphold an exchange rate regime even though it is not the optimal choice or even sustainable in the long run (Eichengreen & Masson 1998), (Juhn & Mauro 2002).

(Frömmel 2010) picks up the relation between credibility and volatility and applies a Markov switching GARCH model to exchange rates of the Visegrád countries between 1994 and their entry to the European Union in 2004. Romania joins the sample as a country that never announced an official peg.

The model allows the coefficients in a GARCH volatility equation (see (Bollerslev 1986)) to switch between two states:⁷

$$\sigma_{t,s_t}^2 = \omega_{s_t} + \alpha_{s_t} \varepsilon_{t-1}^2 + \beta_{s_t} \sigma_{t-1}^2 \quad (4.1)$$

Where the state process s_t follows a time-discrete Markov process with two possible states.⁸ The process is characterized by the transition matrix P and the probability distribution in $t = 1$:

$$P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix}, \quad (4.2)$$

with $p_{ij} = P(s_t = j | s_{t-1} = i)$, and $\Phi_t = \{r_t, r_{t-1}, \dots, r_1; \vartheta\}$ is the set of available information at time t , i.e. the set of all realisations of the returns process up to time t and the vector ϑ of parameters.

The model allows then to distinguish a high and a low volatility state, with the switches between high and low volatility being of particular interest. As pointed out by (Kocenda 2005) a coincidence of switches between volatility states and changes of the officially announced regimes hint at high credibility and primacy of the policy. Figure 2 shows the probabilities of being in the high volatility regime for the five countries. Volatility regimes and policy regimes clearly coincide in the cases of Hungary and Poland. The control by policy was comparatively high, providing some evidence for the success of gradually increasing exchange rate flexibility for exiting a peg (Eichengreen 1999). This is in particular the case when countries have liberalized financial markets, as it is typical for the CEEC's. They need to manage their exposure to international capital accounts and are more vulnerable to being forced off their currency pegs. This high vulnerability of intermediate exchange rate arrangements is also stressed by the results for the Czech Republic and Slovakia, which had to follow the pressure by markets and leave their pegs during currency crises. Accordingly we

⁷ See (Hamilton 1994), p. 237. For details of the model see (Frömmel 2010).

⁸ The model can be easily generalised to k states, as well as the mean process can be modified. This will, however, not lead to substantial changes in the model, so we rely on the simple model as described in the main text.

can observe a switch to the high volatility regime before policy reacted in the course of the crisis. In these cases the markets rather than policy drove the evolution of exchange rate policy.

As a conclusion, the results are strongly in favour of gradually and early widening the bandwidth of currency pegs. Furthermore crawling pegs instead of horizontal ones seem to be advantageous, giving a certain degree of flexibility to react to an evolving environment. The credibility of an exchange rate arrangement is a crucial condition for its success and it is hardly possible to exit smoothly from a peg when markets expect it.

[Insert here: Figure 2: Filter- and smoothed probabilities for EU accession countries]

5. Exchange rate regimes and monetary policy

Exchange rate policy and monetary policy are interdependent. For this reason we will discuss here the monetary policy in the CEEC's, which can (again) be looked at from two different perspectives: the "de jure" and the "de facto" policy.

5.1 Overview of the "de jure" monetary policy in the CEEC's since 1994

In the Czech Republic, the monetary policy initially followed a strategy of jointly targeting the exchange rate and monetary aggregates. Although this policy worked well in the early 1990s, increasing capital inflows made the system unsustainable. After widening the exchange rate band in March 1996, the Czech National Bank (CNB) switched to a managed float in May 1997. Later on, in 1998, monetary policy changed to a strategy of inflation targeting because the CNB considered the demand for money to be too unstable to use a monetary aggregate as an intermediate target (CNB 1998).⁹ However, during the period of inflation targeting, the CNB kept on intervening in the foreign exchange market. (Holub 2004) argues that these interventions in early 1998 and in 1999/2000 are not consistent with inflation targeting. These claims are supported by regular discussions in the central bank's council about the equilibrium exchange rate.¹⁰ An in-depth survey of Czech monetary policy can be found in (Böhm & Zdarsky 2005).

⁹ From 1998 to 2001, the CNB pursued a net inflation target, i.e. headline inflation minus regulated prices and changes in indirect taxes. In 2002 the CNB switched to headline inflation targeting with a continuous and declining target band.

¹⁰ The minutes of the CNB board meeting of December 21, 1999 report that a considerable amount of time was spent discussing exchange rate developments. Board members agreed on the importance of guarding against inadequate appreciation of the koruna's nominal exchange rate. From the minutes of October 26, 2000 meeting: "A large-volume transaction... was responsible for the koruna's strengthening against the euro during the past

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In Hungary the monetary policy concentrated until 2001 on managing the nominal exchange rate within a fairly narrow crawling band (Kiss 2005). During 2001, the National Bank of Hungary (NBH) widened the band substantially. The following transition from a crawling band to a horizontal band coincided with the adoption of inflation targeting. The inflation target is surrounded by a one percent tolerance band, which was achieved until 2002. According to (Dibooglu & Kutan 2001) and (Barlow 2005), the Hungarian policy mix was successful in gaining internal and external stability of the economy.

Until 1998, the National Bank of Poland (NBP) attempted to combine money and exchange rate targets by pursuing a crawling devaluation of the zloty vis-à-vis a basket of currencies. This strategy did not result in both intermediate targets being met in full, but it did facilitate the reduction of inflation initially. Beginning in 1995, Poland experimented with targeting money growth, the interest rate, and the monetary base. However, the NBP did not wait for a crisis to widen the exchange rate band substantially. Due to increased financial market integration, direct inflation targeting was introduced in the last quarter of 1998, although not announced formally until January 1, 1999. Until 2010 the exchange rate didn't play a major role in monetary policy as the NBP didn't intervene on the foreign exchange market. In April 2010 the NBP did intervene, because the strong zloty was considered to be a threat for the economic growth in Poland. The intervention was preceded by more than a month of efforts of the NBP to talk the zloty down. The central bank declared after this intervention that it "can't exclude intervening again".

Although no official commitment is made to any specific exchange rate or inflation path, statements of officials from the National Bank of Romania openly express that monetary policy has aimed at a certain exchange rate path to maintain external competitiveness. The 2001 Annual Report states that the central bank is trying to change this policy: "The support was mainly aimed at enlarging the monetary policy's room for maneuvers through abolishing intensive reliance on the exchange rate as an instrument providing an underpinning to external competitiveness" (NBR 2001). In discussions with the IMF, Romanian authorities have mentioned that they pursue twin objectives of gradual disinflation and maintaining a sustainable external position by using the exchange rate as an implicit nominal anchor (IMF 2003). The Romanian authorities also mentioned the use of an informal euro/ dollar basket,

few days. However, attention was drawn to the fact that, in the present phase of completing state share privatization, this distinct type of divergence could occur again, and even possibly lead to new exchange rate levels. The CNB would carefully monitor and analyze any developments in this direction."

which should be replaced gradually by only the euro as the reference exchange rate on the path to EU accession.

Slovakia focused from the beginning on exchange rate stability, combined with tracking a broad money aggregate, namely M2. Following policies in the Czech Republic, the National Bank of Slovakia (NBS) widened its exchange rate band in January 1997 and changed to a managed float in October 1998. The NBS has used inflation bands as an informal guide for monetary policy since 1999 but the authorities do not consider this strategy to be formal inflation targeting. According to (Beblavy 2002), current monetary policy in Slovakia can be characterized as implicit inflation targeting with a significant amount of discretion. Furthermore, the exchange rate still plays an important role, even though it is officially floating. For example, the stated monetary program for 2000 reports: “NBS expects appreciation pressures. It is ready to intervene ..., the intent of NBS will be to stabilize the foreign exchange rate approximately at the current level” (NBS 1999).

Slovenia's official policy was monetary targeting until switching to a two-pillar strategy similar to that of the European Central Bank in 2001. Within this official framework, the Bank of Slovenia states that it “pursues the core aim of monetary policy, namely price stability, by simultaneously modifying the quantity of money in circulation and the exchange rate. In order to maintain control over the money supply in the face of the free flow of capital, the Bank must adjust interest rates and the exchange rate interdependently” (BOS 2002). However, if the Bank pursues only price stability as its primary objective in a managed floating exchange rate regime, it would not need to adjust exchange rate developments in reaction to capital flows. Rather, the statement reveals implicit dual objectives, namely internal price stability and an exchange rate target.

The Bulgarian policy was over the whole period characterized by a firm focus on a fixed exchange rate. There was one break in the monetary policy in mid-1997, together with the launch of the currency board. The stabilization of inflation and inflation expectations then became also important objectives of the Bulgarian National Bank. Some authors argue that after the introduction of these objectives Bulgaria reached the lowest and most stable inflation rates combined with the highest and most stable output growth since the beginning of the transition process (Hristov & Zaimov 2003). One should however not neglect that Bulgaria was in a period of hyperinflation before the introduction of the above mentioned objectives, which makes a comparison difficult.

In the Baltic States the monetary policy was, because of the currency board arrangements in these countries, characterized by exchange rate targeting. For Estonia there was a strong

focus on the exchange rate since the early nineties (Hartsenko 2002). Latvia and Lithuania were in exactly the same situation (Repse 1999; BOL 2007).

The “de jure” exchange rate policies are summarized in Figure 3. Based on these brief histories, we conclude that, despite the fact that countries announce fairly flexible exchange rate regimes officially, central banks in transition economies pay considerable attention to the exchange rate in monetary policy, which is often embedded in broader macroeconomic programs. In the next section we focus on the research on de facto monetary policy.

[Insert here: Figure 3: “De Jure” Monetary Policy Regimes in CEEC's]

5.2. Research on the de facto monetary policy in the CEEC's

An important tool to analyze the de facto exchange rate regime is the Taylor rule, which was first proposed in 1993. The Taylor rule suggests that interest rates would be changed according to the deviation of inflation from a target and an output gap (Taylor 1993). Other studies often focus on the comparison of the actual setting of policy rates by central banks with what would have been predicted by the Taylor rule as a benchmark. However, as (Peersman & Smets 1999) among others emphasize, the Taylor rule should be perceived as a descriptive instrument to understand the interest rate setting behavior of central banks rather than as a normative guide for monetary authorities. The empirical literature on such interest rate rules for industrial countries has grown significantly during the past decades and has proven the ability of interest rate rules to describe the interest rate setting behaviour of central banks¹¹.

In contrast, research in the context of emerging market economies and particularly transition economies is of more recent origin and relatively scarce. An important finding is that central banks in emerging market economies tend to look beyond inflation and focus on other objectives as well, most prominently on exchange rate changes. (Mohanty & Klau 2004) find that many central banks in their sample of emerging market economies change interest rates systematically in response to exchange rate changes. For some countries the response is even found to be stronger than that to the inflation rate or the output gap.

There are few papers on monetary policy rules in CEEC's. This is due to several reasons. First, the time series available are comparatively short. They usually start in the middle of the 1990s. Second, most CEEC's have not followed one single strategy of monetary policy and

¹¹ For monetary policy rules in the context of inflation targeting see Neumann and von Hagen (2002) and the references therein.

also gradually made their exchange rates more flexible (See Figure 1 and Figure 3). Third, it is not quite clear which target values for inflation the CEEC's followed, as most countries introduced inflation targeting and explicit inflation goals only between 1997 and 2001. The unstable and dynamic economic situation in the CEEC's makes this task even more demanding.

However, there have been recently some attempts to describe the monetary policy in selected CEEC's using interest rate rules: (Maria-Dolores 2005) estimates Taylor rules for the Visegrad countries Czech Republic, Hungary, Poland and Slovakia between 1998 and 2003 and comes to the conclusion that the Taylor rule describes the interest rates well for all countries but Slovakia. Similarly to the original Taylor rule, the rules used by (Maria-Dolores 2005) do not consider exchange rate movements. The lagged interest rate, however, is included. The same set of countries is considered by (Paez-Farell 2007), whereas the sample periods differ from country to country. He compares different versions of interest rate rules and finds that there is a reaction to exchange rate movements. (Angeloni *et al.* 2007) estimate interest rate rules for the Czech Republic, Hungary and Poland from 1995-2004. They introduce the US dollar interest rate as a proxy for inflationary pressures of global origin and dummies for the years preceding the adoption of inflation targeting. (Yilmazkuday 2008) applies Taylor rules to the Czech Republic, Hungary and Poland for the period 1994-2007. He includes the exchange rate in the interest rate rule, but also considers structural breaks. (Moons & Van Poeck 2008) focus on the period 1999-2003 and find that the accession countries do not differ substantially from the current EMU members with respect to the interest rate setting behavior. Furthermore it seems that the potential new entrants have witnessed a notable tendency for increased convergence during the last years. Finally, (Horváth 2009) analyzes the policy neutral rate in the Czech Republic from 2001 to 2006 using a time-varying parameter model with endogenous regressors. The results indicate that the policy neutral rate decreases gradually over the course of the sample period showing a substantial interest rate convergence to levels comparable to the euro area.

All of these studies conclude that a Taylor-like rule is helpful in understanding monetary policy of the CEEC's. However, in most cases inflation coefficients are found to be far below unity, thus violating the so-called Taylor principle. If the Taylor principle holds, the policy rate should move more than one-for-one with increases in the inflation rate and thereby raise the real interest rate. If the monetary policy rule violates the Taylor principle, it will mean that

the central bank does not react adequately on bringing down inflation.¹² This result is counterintuitive as the CEEC's have experienced a remarkable degree of disinflation during the last 15 years. The literature suggests mainly two explanations: (Angeloni *et al.* 2007) argue that part of the reaction on inflation is captured by the coefficient on the US interest rate included in their equation. An increase in global inflation would then lead to a composed reaction, which is partly due to domestic inflation via the conventional inflation coefficient and partly due to foreign inflation via the coefficient on the foreign interest rate. One might similarly argue that the exchange rate included in the interest rate rule partially takes the reaction on inflation, as it anchors expectations on future monetary policy. Another argument, proposed by (Golinelli & Rovelli 2005) is that the reaction to an increase in inflation may be modest, if the initial interest rate compared to inflation was set high enough. Thus a smaller coefficient means that in the course of the disinflation process monetary policy is getting even more aggressive. The scenario seems to be well applicable to the CEEC's. However, one would at least expect the inflation coefficient to be close to unity during periods of autonomous monetary policy.

Besides the above mentioned empirical research, the treatment of exchange rate changes in monetary policy rules is also discussed in the theoretical literature. (Svensson 2000) compares strict inflation targeting (when stabilizing inflation around the inflation target is the only objective for monetary policy) with flexible inflation targeting (when there are additional objectives for monetary policy). His results also indicate that strict inflation targeting implies a vigorous use of the direct exchange rate channel for stabilizing (CPI-) inflation at a short horizon. In contrast, flexible inflation targeting ends up stabilizing inflation at a longer horizon, and thereby also stabilizes real exchange rates and other variables to a significant extent. In comparison with the Taylor rule, the reaction function under inflation targeting in an open economy respond to more information, in particular to foreign disturbances. The particular importance of the exchange rate for monetary policy rules in the case of emerging economies is also stressed by (Amato & Gerlach 2002).

(Taylor 2001) argues that a monetary policy rule that reacts directly to the exchange rate, as well as to inflation and output, sometimes works worse than policy rules that do not react directly to the exchange rate and thereby avoid more erratic fluctuations in the interest rate. In (Taylor 2002), however, he points out that monetary policy in open economies is different from that in closed economies. Open-economy policymakers seem reluctant to considerable

¹² For a more detailed discussion of the Taylor principle see Woodford (2001).

Chapter 1

variability in exchange rate. In his view they should target a measure of inflation that filters out the transitory effects of exchange rate fluctuations and they should also include the exchange rate in their policy reaction functions. He leaves open to further research, whether the exchange rate should appear on the left- or the right-hand side of the rule – that is, whether the policy instrument should be an interest rate or rather a monetary condition index.

(Frömmel *et al.* 2009) extend the existing work on monetary policy rules in CEEC's by splitting up the exchange rate into two components, one of them (b_t) capturing the “technical” reaction to deviations from the central parity in a peg, and the other one (Δs_t) measuring trends in the exchange rate:

$$i_t = r^* + \pi_t + \alpha\pi_t^* + \beta y_t^* + \delta\Delta s_t + \gamma b_t \quad (5.1)$$

With r^* being a long run real exchange rate, π_t the in inflation rate, π_t^* the inflation gap, and y_t^* the output gap. The “band distance” b_t is a nonlinear function of the exchange rate's distance to the edges of the band of a currency peg (if there is one at that time), as shown in Figure 4.

The band distance reflects pressure on the exchange rate, as every time the market rate tends to or actually does exceed one of the borders, the central bank is obliged to react by interventions and/or interest rate changes. This implies that there should be a strong influence of the band distance on the interest rate stance of the monetary policy. The closer the exchange rate comes to the intervention margins the stronger the central bank should react, and the values of b_t increase dramatically during times of crises, when boundaries are reached or exceeded.

[Insert here: Figure 4: The band distance]

[Insert here: Figure 5: The Derivation of the band distance element from the historical exchange rate peg values for Hungary (forint/ Deutsche mark)]

[Insert here: Figure 6: The Derivation of the band distance element from the historical exchange rate peg values for the Czech Republic (Czech Koruna/ Deutsche Mark)]

Figure 5 and Figure 6 show the evolution of the band distance element as an example for Hungary (crawling peg) and the Czech Republic (horizontal peg) respectively. Obviously the

band distance takes in general higher values if the exchange rate pegs are narrow (i.e., during the first parts of the respective sample periods). Furthermore the violation of the band during the Czech exchange rate crisis 1997 substantially increased the pressure on the Czech interest rate policy.

(Frömmel *et al.* 2009) estimate equation (5.1) in a cointegration approach and let the coefficients vary depending on whether the exchange rate regime is classified as “fixed” or “floating” regime. They find that, during the “fixed exchange rate regime” the Taylor principle is violated, but the band distance explains most of the interest rate variation. This is in line with the argument by (Angeloni *et al.* 2007), see above. In contrast, in the “flexible exchange rate regime” for all countries but Slovakia the Taylor principle is fulfilled. Their approach therefore leads to a substantial improvement of empirical results.

Two interesting features stand out. First, the exchange rates of Central and Eastern European countries often had appreciating pressure during fixed regimes and therefore, were close to the strong edge of the narrow bands (see Figure 5 and Figure 6). Second, the values increase dramatically during times of crises, when boundaries are reached or exceeded (see Figure 6).

6. Exchange rate regimes and interventions

Monetary policy influences the exchange rate. In this section we review how central bank interventions and central bank communication can influence the exchange rate. A basic insight of the research on central bank interventions (for surveys see e.g. (Sarno & Taylor 2001; Vitale 2007)) is that interventions are able to move the exchange rate. They affect the first two moments of the exchange rate (Scalia 2008) and the impact is usually stronger in emerging than in developed countries (Canales-Kriljenko 2003). This may be due to less sterilization, the market's size and organization.

Besides direct interventions central bank communication may also be seen as a form of intervention, that is – although less obvious at first sight – able to affect the exchange rate as well (Ehrmann & Fratzscher 2007). There is a huge amount of research providing some ambiguous empirical evidence on an exchange rate impact of central bank communication (see the survey in (Blinder *et al.* 2008)). The impact of verbal interventions or communication stems from their role in anchoring expectations on future monetary policy, i.e. the signaling or expectation channel of monetary policy (Sarno & Taylor 2001), but also by functioning as a

coordination advice for market participants (Reitz & Taylor 2008). Thus, communication may complement intervention or substitute it (Fratzscher 2008).

Due to the more dynamic economic environment in a transition economy verbal interventions may be more effective than in developed markets. However, again most of the work deals with developed markets, mostly for the FOMC, the ECB, the Bank of England and the Bank of Japan, and there are only few papers that focus on transition economies: (Rozkrut et al. 2007) find for the Czech Republic, Hungary and Poland, that speeches about monetary policy affect the exchange rate. (Égert 2007) finds influence of central bank communication for Hungary, but not for other CEEC's. He also concludes that the Hungarian National Bank (MNB) used actual interventions very rarely, but mainly relies on verbal interventions. The latter is also analyzed by (Frömmel *et al.* 2010) who estimate the impact of communication by central bankers and politicians on high-frequency exchange rates. They find that central bank communication mainly affects the exchange rate indirectly via order flow, i.e., signed transaction volume.

7. Conclusion

The exchange rates of CEEC's have been subject of numerous studies. In this selective survey we have described the evolution of exchange rate arrangements of CEEC's and reviewed four aspects of their exchange rate policy: the deviation of de facto from de jure exchange rate regimes, the relation between exchange rate volatility and exchange rate arrangements, the inclusion of exchange rates in monetary policy rules and the intervention policy of CEEC's.

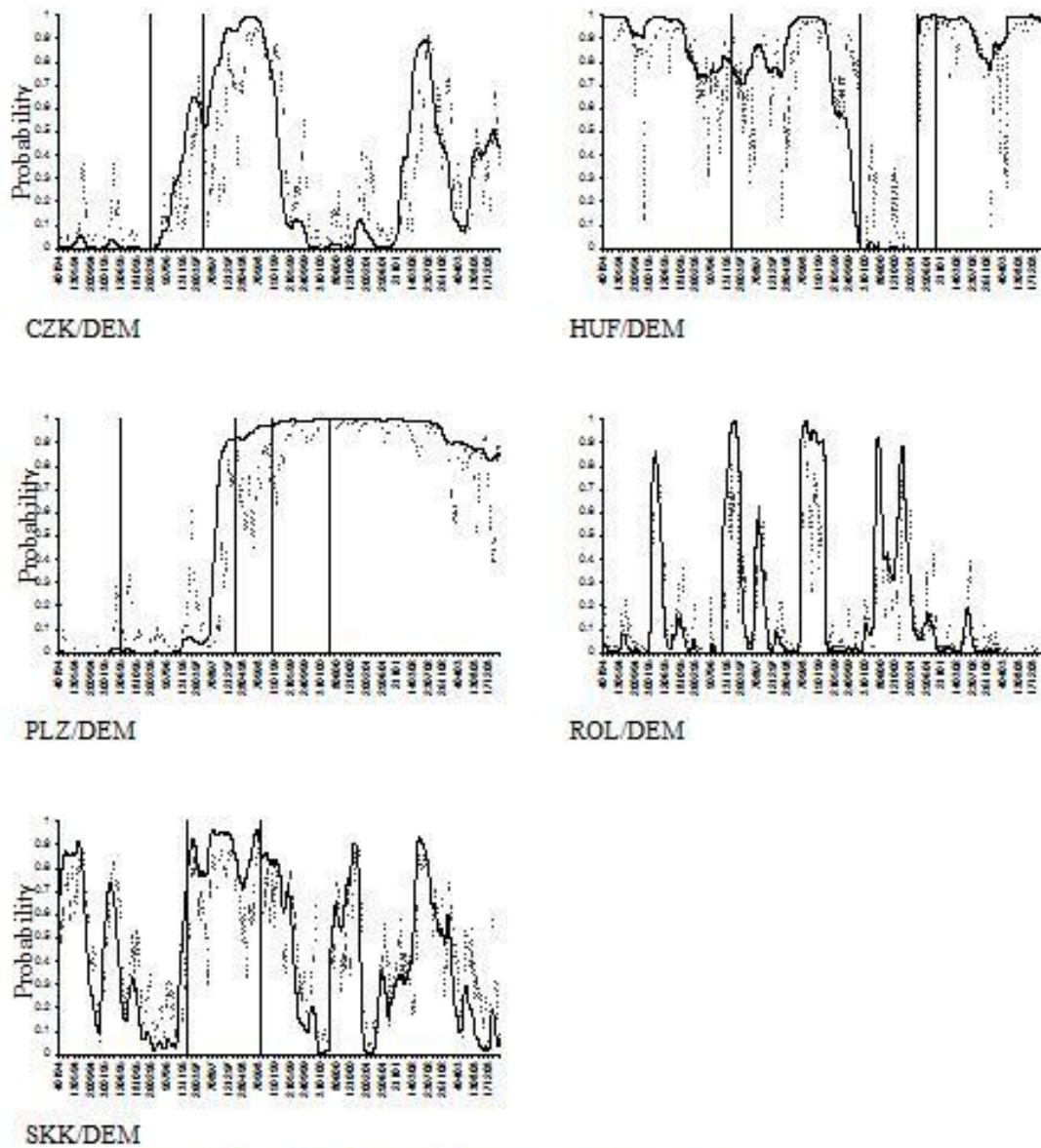


Figure 2: Filter- and smoothed probabilities for EU accession countries
 The bold lines are the smoothed probabilities $P(s_t=1 | \Phi_T)$ of being in the high volatility regime, the dotted lines reflect the filter probabilities $P(s_t=1 | \Phi_t)$ of being in the high volatility regime 1. The smoothed probabilities correspond with an ex post analysis, whereas the filter probabilities are the probabilities as observed on the respective day. The vertical lines represent changes in the exchange rate system of the respective country. Source: (Frömmel 2010)

Country	Regime Objective(*)	Exchange Rate + Mon. Targeting		Exchange Rate + Inflation Targeting															
		Credit volume and M2	Net inflation (a)	Headline inflation (linear and declining target band)	Inflation Targeting														
Bulgary	Regime Objective(*)	Exchange Rate + Monetary Targeting		Exchange Rate Targeting															
Czech Rep.	Regime Objective(*)	Exchange Rate + Monetary Targeting		Inflation Targeting															
Estonia	Regime Objective(*)	Exchange Rate Targeting		Exchange Rate Targeting															
Hungary	Regime Objective(*)	Exchange Rate Targeting		Inflation Targeting															
	Regime Objective(*)	Exchange Rate Targeting		CPI annual average															
Latvia	Regime Objective(*)	Exchange Rate Targeting		Exchange Rate Targeting															
	Regime Objective(*)	Exchange Rate Targeting		Exchange Rate Targeting															
Lithuania	Regime Objective(*)	Exchange Rate + Monetary Targeting		Inflation Targeting															
	Regime Objective(*)	Exchange Rate + Monetary Targeting		End of the year CPI inflation															
Poland	Regime Objective(*)	Exchange Rate Targeting		Exchange Rate + Inflation Targeting															
	Regime Objective(*)	Exchange Rate Targeting		Exchange Rate + Inflation Targeting															
Romania	Regime Objective(*)	Monetary Targeting		Exchange Rate + Monetary Targeting															
	Regime Objective(*)	Monetary Targeting		Exchange Rate + Monetary Targeting															
Slovak Rep.	Regime Objective(*)	Exchange Rate + Monetary Targeting		Exchange Rate + Inflation Targeting															
	Regime Objective(*)	Exchange Rate + Monetary Targeting		Exchange Rate + Inflation Targeting															
		1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010

(*) If available we included the inflation or monetary target variable

(a) Net Inflation = Headline Inflation minus regulated prices and changes in indirect taxes

Figure 3: "De Jure" Monetary Policy Regimes in CEEC's

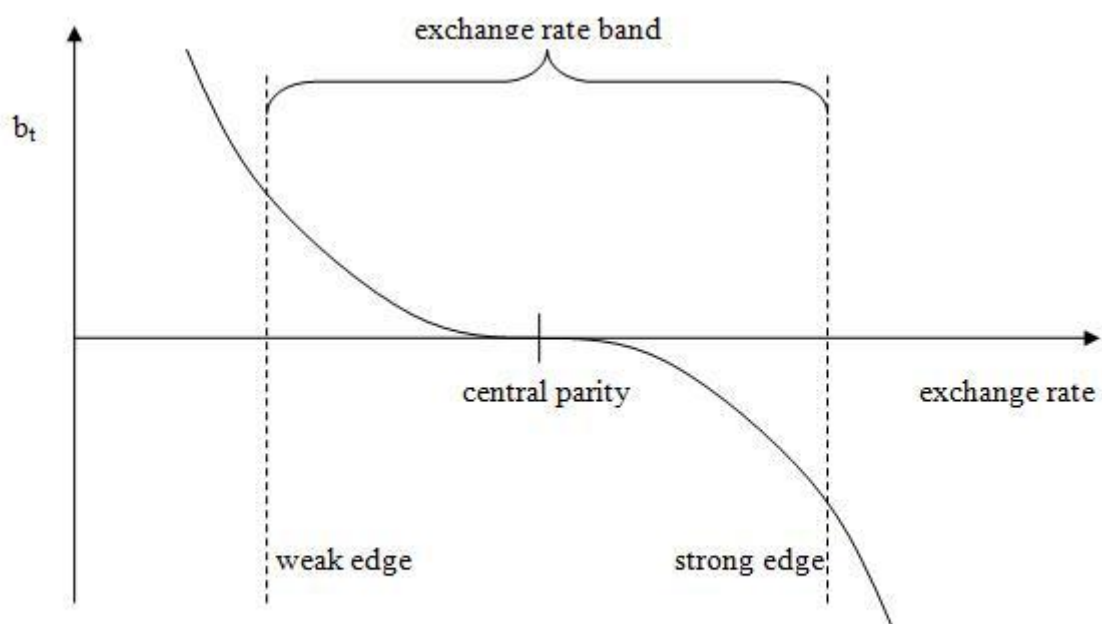


Figure 4: The band distance

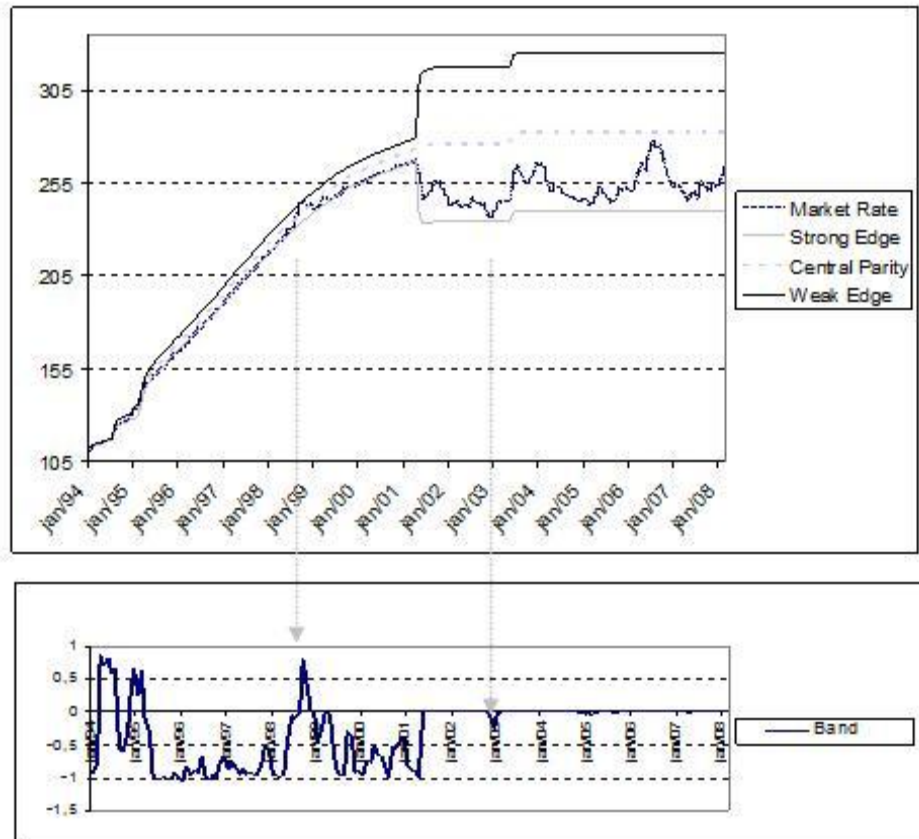


Figure 5: The Derivation of the band distance element from the historical exchange rate peg values for Hungary (Forint/ Deutsche Mark)

Source: (Frömmel *et al.* 2009)

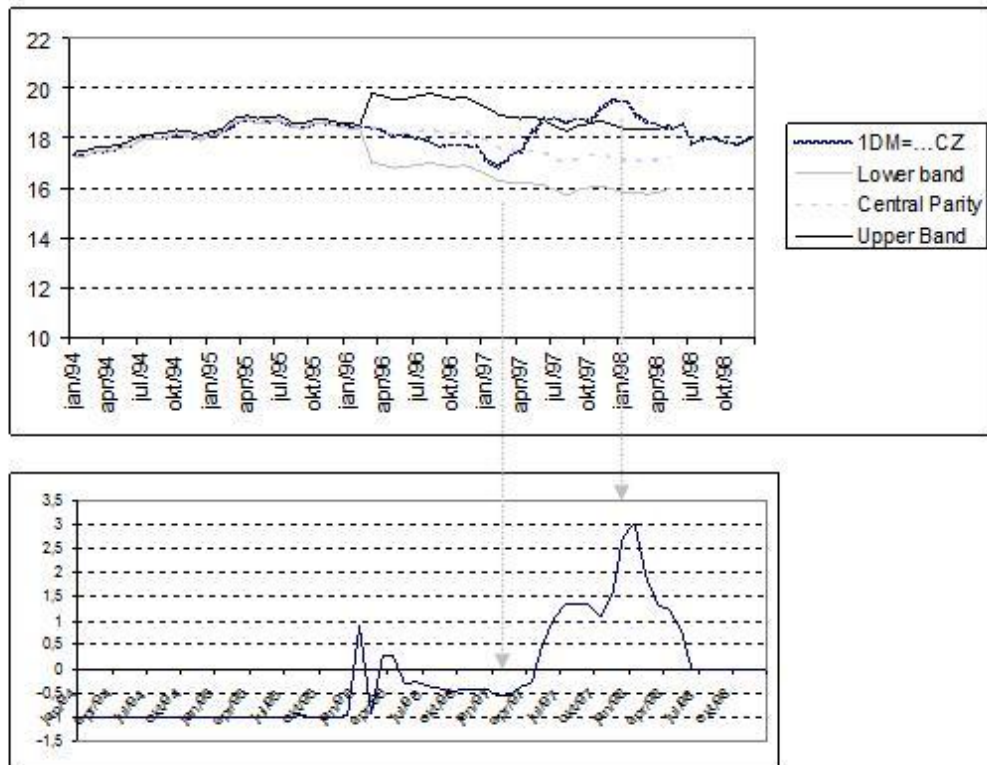


Figure 6: The Derivation of the band distance element from the historical exchange rate peg values for the Czech Republic (Czech Koruna/ Deutsche Mark)

Source: (Frömmel *et al.* 2009)

LIST OF REFERENCES

- Amato, J.A., Gerlach, S., 2002. Inflation Targeting in Emerging Market and Transition Economies: Lessons after a Decade. *European Economic Review* 46, 781-790
- Angeloni, I., Flad, M., Mongelli, F.P., 2007. Monetary Integration of the New EU Member States: What Sets the Pace of Euro Adoption? *Journal of Common Market Studies* 45, 367-409
- Ball, L., 1999. Policy rules for open economies. University of Chicago Press, Chicago.
- Barlow, D., 2005. The Hungarian Exchange Rate and Inflation over the Transition. *Economic Systems*, 87-97
- Beblavy, M., 2002. Exchange Rate and Exchange Rate Regime in Slovakia: Recent Developments. *European Center Working Paper on Macroeconomic Studies*
- Bénassy-Quéré, A., 1996. Potentialities and opportunities of the euro as an international currency. *CEPII Report for the European Commission*
- Berger, H., Sturm, J.-E., De Haan, J., 2000. An empirical investigation into exchange rate regime choice and exchange rate volatility. *CESifo Working Paper Series*
- Blinder, A.S., Ehrmann, M., de Haan, J., Fratzscher, M., Jansen, D.-J., 2008. Central Bank Communication and Monetary Policy: A Survey of Theory and Evidence. *ECB Working Paper Series*
- Böhm, J., Zdarsky, V., 2005. Conducting Monetary Policy in a Small Open Economy under Globalized Capital Markets: The Experience of the Czech Republic. *BIS Papers*, 141-149
- BOL, 2007. Annual Report 2007 of the BOL (Bank of Lithuania). *Annual Reports*, 25-29
- Bollerslev, T., 1986. Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics* 31, 302-327
- BOS, 2002. BOS (Bank of Slovenia) Annual Report 2002.
- Calvo, G.A., Reinhart, C.M., 2002. Fear of floating. *Quarterly Journal of Economics* 117, 379-408
- Canales-Kriljenko, J.I., 2003. Foreign Exchange Intervention in Developing and Transition Economies: Results of a Survey. *IMF Working Paper Series*
- CNB, 1998. CNB (Czech National Bank) Annual Report.
- Corker, R., Beaumont, C., van Elkan, R., Iakova, D.M., 2000. Exchange rate regimes in selected advanced transition economies - Coping with transition, capital inflows and EU accession. . *IMF Policy Discussion Papers PDP/00/03*
- De Grauwe, P., 2003. The economics of monetary union. Oxford University Press, Oxford.
- Dibooglu, S., Kutan, A., 2001. Sources of Real Exchange Rate Fluctuations in Transition Economies: The Case of Hungary and Poland. *Journal of Comparative Economics*, 257-275
- Duttagupta, R., Fernandez, G., Karacadag, C., 2004. From fixed to float: Operational aspects of moving towards exchange rate flexibility. *IMF Working Paper Series*
- Égert, B., 2007. Central Bank Interventions, Communication and Interest Rate Policy in Emerging European Economies. *Journal of Comparative Economics* 35, 387-413
- Ehrmann, M., Fratzscher, M., 2007. Communication by Central Bank Committee Members: Different Strategies, Same Effectiveness? *Journal of Money, Credit and Banking* 39, 509-541
- Eichengreen, B., 1999. Kicking the Habit: Moving from Pegged Rates to Greater Exchange Rate Flexibility. *Economic Journal*, C1-C14
- Eichengreen, B., Hausmann, R., 1999. Exchange rates and financial fragility. *NBER Working Papers* 7418
- Eichengreen, B., Masson, P., 1998. Exit strategies: Policy options for countries seeking greater exchange rate flexibility. *IMF Occasional Papers* 168

- Fidrmuc, J., Horváth, R., 2008. Volatility of exchange rates in selected new EU members: Evidence from daily data. *Economic Systems* 32, 103-118
- Fischer, S., 2001. Exchange Rate Regimes: Is the bipolar view correct? *Journal of Economic Perspectives* 15, 3-24
- Flood, R.P., Rose, A.K., 1999. Understanding exchange rate volatility without the contrivance of macroeconomics. *Economic Journal* 109, 660-672
- Flood, R.P., Rose, A.K., 2005. A new approach to asset integration: methodology and mystery. *Pacific Economic Review*
- Frankel, J.A., Fajnzylber, E., Schmukler, S.L., Servén, L., 2001. Verifying exchange rate regimes. *Journal of Development Economics* 66, 351-386
- Frankel, J.A., Wei, S.-J., 1992. Yen bloc or dollar bloc? Exchange rate policies in the East Asian economies. In: Takatoshi I & Krueger A (eds.) *Macroeconomic linkages: Savings, Exchange rates and Capital Flows*. University Press of Chicago, Chicago.
- Fratzscher, M., 2008. Oral Interventions versus Actual Interventions in FX Markets - An Event Study Approach. *Economic Journal* 118, 1079-1106
- Frömmel, M., 2010. Volatility Regimes in Central and Eastern European Countries' Exchange Rates. *Czech Journal of Economics and Finance*
- Frömmel, M., Garabedian, G., Schobert, F., 2009. Monetary Policy Rules in Central and Eastern European Countries: Does the Exchange Rate Matter? Ghent University Working Paper Series
- Frömmel, M., Kiss, M., Pintér, K., 2010. Central Bank Communication, Macroeconomic Announcements, and Order Flow: An Analysis of the Hungarian Foreign Exchange Market. *International Journal of Finance & Economics*
- Frömmel, M., Menkhoff, L., 2001. Risk reduction in the EMS: Evidence from exchange rate properties. *Journal of Common Market Studies* 39, 285-306
- Frömmel, M., Menkhoff, L., 2003. Increasing exchange rate volatility during the recent float? *Applied Financial Economics* 13
- Frömmel, M., Schobert, F., 2006. Exchange Rate Regimes in Central and East European Countries: Deeds vs. Words. *Journal of Comparative Economics* 34, 467-483
- Golinelli, R., Rovelli, R., 2005. Monetary Policy Transmission, Interest Rate Rules and Inflation Targeting in Three Transition Countries. *Journal of Banking and Finance*, 183-201
- Haldane, A.G., Hall, S.G., 1991. Sterling's relationship with the dollar and the deutschemark: 1976-89. *Economic Journal* 101, 436-443
- Halpern, L., Wyplosz, C., 1997. Equilibrium exchange rates in transition economies. *IMF Staff Papers*, 430-461
- Hamilton, J., 1994. *Time Series Analysis*. Princeton University Press, Princeton.
- Hartsenko, J., 2002. Estonian Monetary System and Banking Development on Way to the Euro Zone. Effect of Accession to the European Union on the Economic Policy of Estonian. In: *Scientific and Educational Conference*, pp. 65-71. Berlin Verlag Arno Spitz GmbH, Berlin
- Hausmann, R., Panizza, U., Stein, E., 2001. Why do countries float the way they float. *Journal of Development Economics* 66, 387-414
- Holub, T., 2004. Foreign Exchange Interventions under Inflation Targeting: The Czech Experiences. CNB (Czech National Bank) Internal Research and Policy Note
- Horváth, R., 2009. The time-varying policy neutral rate in real-time: A predictor for future inflation? *Economic Modelling* 26
- Hristov, K., Zaimov, M., 2003. Shadowing the euro: Bulgaria's monetary policy five years on.
- Hughes-Hallett, A., Anthony, M.L., 1997. Exchange rate behaviour under the EMS regime: Was there any systematic change? *Journal of International Money and Finance* 16, 537-560

- IMF, 2003. IMF Country Report.
- Juhn, G., Mauro, P., 2002. Long-run determinants of exchange rate regimes: A simple sensitivity Analysis. IMF Working Paper Series 02/104
- Kiss, G., 2005. Monetary policy issues in Hungary on the eve of EU membership.
- Kóbor, Á., Székely, I., 2004. Foreign exchange market volatility in EU accession countries in the run-up to Euro adoption: Weathering uncharted waters. *Economic Systems* 28, 337-352
- Kocenda, E., 1998. Altered band and exchange volatility. *Economics of Transition* 6, 173-181
- Kocenda, E., 2002. Exchange rate movements in European transition economies. Nova Science, New York.
- Kocenda, E., 2005. Beware of breaks in exchange rates: Evidence from European Transition Countries. *Economic Systems* 29, 307-324
- Krugman, P.R., 1991. Target zones and exchange rate dynamics. *Quarterly Journal of Economics* 106, 669-682
- Levy-Yeyati, E., Sturzenegger, F., 2005. Classifying exchange rate regimes: Deeds vs. words. *European Economic Review*, 1603-1635
- Maria-Dolores, R., 2005. Monetary Policy Rules in Accession Countries to EU: Is the Taylor Rule a Pattern? *Economic Bulletin* 5, 1-16
- McKinnon, R., Schnabl, G., 2004. The East Asian dollar standard, fear of floating and original sin. *Review of Development Economics*, 331-360
- Mohanty, M.S., Klau, M., 2004. Monetary Policy Rules in Emerging Market Economies: Issues and Evidence. BIS Working Papers
- Moons, C., Van Poeck, A., 2008. Does One Size Fit All? A Taylor-rule Based Analysis of Monetary Policy for Current and Future EMU Members. *Applied Economics* 40, 193-199
- Mussa, M., Masson, P., Swoboda, A., Jadresic, E., Mauro, P., Berg, A., 2000. Exchange rate regimes in an increasingly integrated world economy. IMF Occasional Papers
- NBR, 2001. NBR (National Bank of Romania) Annual Report 2001. 63
- NBS, 1999. NBS (National Bank of Slovakia) Menovy Program na Rok 2000 (Exchange Rate Program for the Year 2000).
- Obstfeld, M., 1997. Destabilizing effects of exchange-rate escape clauses. *Journal of International Economics* 43, 61-77
- Obstfeld, M., Rogoff, K., 1995. The mirage of fixed exchange rates. *Journal of Economic Perspectives*, 73-96
- Paez-Farell, J., 2007. Understanding Monetary Policy in Central European Countries using Taylor-type Rules: The Case of the Visegrad Four. *Economics Bulletin* 5, 1-11
- Peersman, G., Smets, F., 1999. The Taylor Rule: A Useful Monetary Policy Benchmark for the Euro Area. *International Finance* 2, 85-116
- Popper, H., Lowell, J., 1994. Officially floating, implicitly targeted exchange rates: Examples from the Pacific Basin. In: Glick R & Hutchison M (eds.) *Exchange rate policy and interdependence: Perspectives from the Pacific Basin*. Cambridge University Press, Cambridge.
- Reinhart, C.M., Rogoff, K., 2004. The modern history of exchange rate arrangements: A reinterpretation. *Quarterly Journal of Economics*, 1-48
- Reitz, S., Taylor, M.P., 2008. The Coordination Channel of Foreign Exchange Intervention: A Nonlinear Microstructural Analysis. *European Economic Review* 52, 55-76
- Repse, E., 1999. Speech on monetary policy in Latvia and exchange rate strategies. In: *Central Bank Articles and Speeches*. BIS, Basel
- Rogoff, K., Husain, A.M., Mody, A., Brooks, R., Oomes, N., 2004. Evolution and performance of exchange rate regimes. IMF Occasional Papers

- Rozkrut, M., Rybinski, K., Sztaba, L., Szwaja, R., 2007. Quest for Central Bank Communication: Does it Pay to be Talkative? *European Journal of Political Economy* 23, 176-206
- Sachs, J.D., 1996. Economic transition and the exchange rate regime. *American Economic Review* 86, 147-152
- Sarno, L., Taylor, M.P., 2001. Official Intervention in the Foreign Exchange Market: Is It Effective, and if so, How Does It Work? *Journal of Economic Literature*, 839-868
- Scalia, A., 2008. Is Foreign Exchange Intervention Effective? Some Microanalytical Evidence from the Czech Republic. *Journal of International Money and Finance*, 529-546
- Schnabl, G., 2004. De jure vs. de facto exchange rate stabilization in Central and Eastern Europe. *Aussenwirtschaft* 59, 171-190
- Stancík, J., 2007. Determinants of exchange rate volatility: The case of the new EU members. *Czech Journal of Economics and Finance* 57, 414-432
- Svensson, L.E.O., 2000. Open-economy Inflation Targeting. *Journal of International Economics* 50, 155-183
- Szapáry, G., Jakab, Z., 1998. Exchange rate policy in transition economies: The case of Hungary. *Journal of Comparative Economics* 26, 691-717
- Taylor, J.B., 1993. Discretion versus Policy Rules in Practice. *Carnegie-Rochester Conference Series on Public Politics*, 195-214
- Taylor, J.B., 2001. The Role of the Exchange Rate in Monetary Policy Rules. *The American Economic Review* 91, 263-267
- Taylor, J.B., 2002. The Monetary Transmission Mechanism and the Evaluation of Monetary Policy Rules In: Loayza N & Schmidt-Hebbel K (eds.) *Monetary Policy: Rules and Transmission Mechanisms*. Central Bank of Chile, pp. 21-46.
- Vitale, P., 2007. A Guided Tour of the Market Microstructure Approach to Exchange Rate Dermination. *Journal of Economic Surveys*, 903-934
- Yilmazkuday, H., 2008. Structural Breaks in Monetary Policy Rules: Evidence from Transition Countries. *Emerging Markets Finance and Trade* 44, 87-97

Chapter 2

**News, Liquidity Dynamics and
Intraday Jumps: Evidence from the
HUF/ EUR Market**

News, Liquidity Dynamics and Intraday Jumps: Evidence from the HUF/EUR Market*

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Abstract

We study intraday jumps on a pure limit order FX market by linking them to news announcements and liquidity shocks. First, we show that jumps are frequent and contribute greatly to the return volatility. Nearly half of the jumps can be linked with scheduled and unscheduled news announcements. Furthermore, we show that jumps are information based, whether they are linked with news announcements or not. Prior to jumps, liquidity does not deviate from its normal level, nor do liquidity shocks offer any predictive power for jump occurrence. Jumps emerge not as a result of unusually low liquidity but rather as a result of an unusually high demand for immediacy concentrated on one side of the book. During and after the jump, a dynamic order placement process emerges: some participants endogenously become liquidity providers and absorb the increased demand for immediacy. We detect an interesting asymmetry and find the liquidity providers to be more reluctant to add liquidity when confronted with a news announcement around the jump. Further evidence shows that participants submit more limit orders relative to market orders after a jump. Consequently, the informational role of order flow becomes less pronounced in the thick order book after the jump.

JEL: F31, G15

Keywords: microstructure, foreign exchange, jumps, liquidity, Hungary, limit order book

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News, Liquidity Dynamics and Intraday Jumps: Evidence from the HUF/EUR Market

1. Introduction

Jumps, which are significant discontinuities in asset prices, have been an important topic in financial research over the last few decades. Empirical research shows that jumps in financial time series are common and contribute greatly to asset volatility. As an integral part of the underlying price process, they pose extreme price risk for traders and they are of vital importance for risk management purposes.

Our study investigates intraday jumps on the exchange market and their relation to macroeconomic news releases and the liquidity dynamics of the limit order book. We study the interbank HUF/ EUR exchange market over a two-year sample period (2003 and 2004). First, we detect jumps and document their prevalence and size on an emerging foreign exchange market, which is characterized by relatively low trading volumes. In previous research, jumps have been related with macroeconomic news of various sorts. We investigate to what extent these results also hold for this market. Besides scheduled macroeconomic announcements, we also incorporate real-time, unscheduled announcements in our dataset. Furthermore, it has been put forward by Lahaye *et al.* (2011) that jumps which cannot be related to news announcements can be caused by insufficient market liquidity.

However, the concept of liquidity is elusive as it has multiple dimensions (Amihud 2002; Pástor & Stambaugh 2003; Acharya & Pedersen 2005). For example, Liu (2006) defines liquidity as the ability to trade large quantities quickly at low cost and with little price impact. Four dimensions, namely trading quantity (depth), trading speed (immediacy), trading cost (tightness), and price impact (resiliency) emerge from this definition. As one of our motives is to pin down the cause of the jump, we map the different dimensions of liquidity that can be observed in the limit order book, and investigate whether there is any systematic pattern prior to the jump. We find that the jump itself influences the behavior of market participants, and we shed a new light on how traders formalize their “make or take” decision during and after a jump. We link our work with empirical regularities regarding traders’ order placement strategy, and investigate to what extent they still hold under extreme market conditions.

By definition, jumps are latent as they are an integral part of the price process, which makes them difficult to estimate. In their seminal work, Barndorff-Nielsen and Shephard

(2004) show that under maintained conditions the quadratic variation process could be decomposed into an integrated variation component and a jump component. Moreover, they provide two non-parametric measures of volatility designed for the discrete nature of empirical high-frequency data: realized variance and realized bipower variation. The former measures the quadratic variation while the latter measures the integrated variation. The difference between the two provides a consistent estimate of the jump component under maintained conditions. In their later work, Barndorff-Nielsen and Shephard (2006b) propose several finite sample jump detection statistics based on asymptotic distribution theory. Huang and Tauchen (2005) further provide extensive simulation evidence in support of the finite sample properties of these jump test statistics. The jump detection method has been applied in empirical researches of various settings. For example, Andersen *et al.* (2007a) confirm the existence of jumps in FX, equity and treasury markets and make important progress in the forecasting realized volatility by separating the jump component from its continuous sample path counterpart. Beine *et al.* (2007) find that coordinated interventions by central banks in FX markets cause fewer but more pronounced jumps after accounting for the announcement effect.

More recently, various attempts have been made to modify the jump identification method, so that it can pin down the exact timing of the jump at the intraday level. Andersen *et al.* (2007b) and Andersen *et al.* (2010) present a recursive jump detection method for identifying intraday jumps, thereby providing superior information on jumps. Alternative methods to detect intraday jumps have also been presented by Lee and Mykland (2008), Jiang *et al.* (2011) and Boudt and Petitjean (201x) among others.

The advances made in jump detection methods enjoy a burst of recent analysis on the link between macroeconomic fundamentals (news) and jumps on various financial markets. Huang (2007) confirms that jumps occur more frequently on news-days than on non-news days in US futures market. Focusing on US treasury market, Dungey *et al.* (2009) find that the majority of cojumps are associated with scheduled news releases, which is later confirmed by Jiang *et al.* (2011). Placing more emphasis on the general regularity of jump dynamics across different asset markets (US stock, Treasury and USD/EUR market), Evans (2011) documents that around one-third of the intraday jumps occur immediately after the release of news and that the informational shocks explain large proportions of the jump magnitude. In their seminal work, Lahaye *et al.* (2011) analyze the difference in size, frequency and timing of jumps across three US stock index futures, one treasury bond futures and four major currency pairs, and further link these dynamics to their likely sources (such as informational shocks).

Several stylized facts emerge from their work: first, foreign exchange markets experience significantly more jumps while the average jump magnitude is smaller compared to other asset markets. Second, the link between macroeconomic news and jumps is weaker in foreign exchange markets than in other asset markets, which Lahaye *et al.* (2011) attribute to the restricted news dataset and other possible sources of jumps such as idiosyncratic liquidity shocks commonly observed in the currency markets during the slow trading process.

Related high frequency studies have also examined the relation between liquidity dynamics of the market and jumps. Bajgrowicz and Scaillet (2011) find that trading volume, as a rough gauge of market liquidity, explains independently a small portion of jumps in the US stock market, as trading volume reaches its highest value during the 5 minute interval prior to the jump. Using a probit model, Jiang *et al.* (2011) confirm that lagged liquidity shocks are able to predict the occurrence of jumps after accounting for the effect of informational shocks. Using an event study approach, Boudt and Petitjean (201x) document that jumps are largely driven by a sharp rise in the demand for immediacy, as the number of trades increases dramatically prior to jumps, while market depth at the best price does not decay as commonly expected. To sum up, potential economic sources of jumps in financial markets include scheduled macroeconomic news, unscheduled news releases, and market liquidity shocks.

An independent strand in the microstructure literature has focused on investors' order submission strategies in limit order book markets: the classical "make or take" decisions (see Bloomfield *et al.* 2005, among others). On the theory side, Cohen *et al.* (1981), Glosten (1994), Seppi (1997), Harris (1998), Parlour (1998), Foucault (1999), Sandås (2001), Hollifield *et al.* (2004), Foucault *et al.* (2005) and Roşu (2009) develop liquidity-based models of limit-order book. The main predictions of these models include that (1) the proportion of limit orders relative to market orders increases subsequent to a rise in asset volatility, (2) the proportion of limit orders relative to market orders increases subsequent to the widening of spreads, and (3) own side depth encourages the submission of market orders. On the empirical side, Biais *et al.* (1995), Griffiths *et al.* (2000), Ahn *et al.* (2001), Rinaldo (2004) and Cao *et al.* (2008) have provided consistent evidence with these predictions. More recently, experimental and empirical studies based on information-based models of the limit order book uniformly suggest that informed traders tend to use, under certain conditions, limit orders at the side where liquidity is needed (see Bloomfield *et al.* 2005; Kaniel & Liu 2006 , among others). Bloomfield *et al.* (2005) posit that, under certain conditions, informed traders

change their order aggressiveness over the trading period by submitting limit orders at the side where liquidity is scarce as they are less subject to adverse selection costs.

Jumps are sudden price spikes that pose significant price risk to investors. Obviously, it is interesting to examine traders' "make or take" decisions under these extreme market conditions. Moreover, it is of great interest to test whether the predictions regarding traders' order placement strategy still hold conditioning on the occurrence of jumps with and without macroeconomic news. In spite of the relevance of the topic, there are to the best of our knowledge no works that investigate the order placement strategies around intraday jumps.

Our article contributes to the empirical studies on jumps in at least three ways: First, we apply an established jump identification method to a small and less liquid exchange rate market in contrast to existing work which focuses on the most liquid major currency pairs such as USD/EUR and USD/GBP. Our aim is to examine to which extent the jump dynamics exhibited in these major currencies could be generalized to the other currencies, in particular the Hungarian forint. One could expect jumps would be more prevalent in the HUF/EUR market than in major exchange rate markets due to its illiquidity and relatively small market capitalization as examined in Frömmel *et al.* (2011). Our results confirm that jumps are large and prevalent in a relatively illiquid market such as HUF/EUR market. Around 18.2% of our sample days are identified as containing at least one intraday jump with the jump component contributing nearly one-half of the realized volatility during these jump days.

Secondly, we extend the announcement effect literature by investigating the link between jumps and news releases of various sorts. Our enlarged news dataset covers not only the scheduled macroeconomic news announcements, but also the unscheduled news announcements which will change investors' expectation on future fundamentals. The enlarged news dataset also enables us to (informally) compare the relative importance of different news categories. Our results suggest that both scheduled and unscheduled news are related to jumps with the unscheduled news such as polls, surveys, forecasts and analysis on (future) fundamentals producing the most of the jumps (30.4%).

Thirdly, to the best of our knowledge, our work is the first to bridge the gap between jump-related literature and the order placement literature. Using event study methodology, we zoom in on the dynamics of various liquidity dimensions around jumps, providing a comprehensive picture on how the limit order book looks like before, during and after the jump. We are the first to do this for this type of analysis for the foreign exchange market. Furthermore, we test whether the predictions from limit order book models for order placement still hold under these extreme market conditions. We find only a very weak, if any,

pattern in liquidity prior to jumps after controlling for the announcement effect. Consistent with Boudt and Petitjean (201x), we find that jumps do not emerge as a result of unusually low liquidity, but as a result of an unusually high demand for immediacy concentrated on one side of the limit order book, implying increased information asymmetry across traders during the jump period. Moreover, more limit orders are added to the ask (bid) side subsequent to a positive (negative) jump, confirming the existence of discretionary liquidity providers who supply liquidity at the side where it is needed the most. We also observe an interesting asymmetry in post-jump resiliency, which is clearly higher for negative jumps than for positive jumps. Finally, we perform an additional regression-type analysis to show that post-jump transaction order flow is less informative, as more limit orders relative to market orders are submitted to the order book subsequent to jumps. Overall, our results confirm the predictions from limit order book models: the submission of limit orders is encouraged by the widening of the spread and increased volatility caused by a jump.

To presage our results, the rest of the paper proceeds as follows. Section 2 describes a pure order-driven FX market in general and our unique dataset in particular. Section 3 explains our theoretical framework regarding the jump detection method. Section 4 presents our empirical findings regarding the jump dynamics and the announcement effect. Section 5 presents our event-study results on the liquidity dynamics around jumps. Section 6 provides further evidence on pre-jump and post-jump liquidity patterns. Section 7 concludes.

2. Data

The foreign exchange market

The foreign exchange market is a two-tier market. Trades on the foreign exchange market can be divided into customer trades, i.e. trades between a bank and customers (the ultimate end-users, for instance importing and exporting firms, mutual or hedge funds, governments and central banks) and interbank trades. In this work we focus on the interbank market, to which customers do not have access. It is here that the price formation takes place. The market is a pure order-driven market, without designated market maker. Participants can submit orders 24h a day. The majority of trades on this market are nowadays done via electronic broking systems. Since their introduction in 1992 their share in total transaction

volume has steadily increased, depending on the country, from 4 to 6 per cent in 1995 to more than 55% of the interbank market in 2010 (BIS 1996, 2010).¹⁴

There are two main platforms competing in the foreign exchange market: Reuters D3000 and EBS (Electronic Broking System). In our analysis we rely on the Reuters D3000 system. As an electronic limit order book it contains buy and sell orders in a price-time priority. Euro sale and purchase offers are placed at limit prices. Besides these limit orders, consisting of the maximum respectively minimum price and the quantity offered to be traded, it is also possible to place a market order, i.e., an order without a specified price. They are immediately matched with the best corresponding limit order and thus more aggressive. While limit orders add liquidity to the limit order book, market orders take liquidity from the book. The following matches may lead to a trade: two limit orders that are matched up by the system, or a market order that is matched up with the best limit order on the opposite side.

The HUF/EUR market

Our dataset consists of all quotes, i.e., limit and market orders, on the HUF/EUR interbank market that have been placed during the years 2003 and 2004 via the Reuters D3000 broking system. Because at this time the competing system EBS did not offer services for the HUF/EUR market, the dataset covers the complete trading on electronic brokerage platforms, and thus the major part of the total market activity (which would also include OTC trades). The HUF trade accounted during our sample period for only 0.22% of the global turnover on the FX market (BIS 2005). This dataset was also described in Gereben and Kiss M. (2006). In Table 1 we present various summary statistics for the activity on this market, such as the number of quotes and trades and the distribution over trade size for the whole sample period and for each year individually.

The reconstruction of the limit order book

Our dataset contains the price, the quantity in euro that was offered or asked, whether it was a market or a limit order and the exact time when the order was placed and when it disappeared. We observe whether the order was withdrawn or whether it was executed, i.e., matched with another limit or market order. We do not observe the identity of the traders. Our analysis requires information on the state of the limit order book at the intraday level. We therefore reconstruct the order book, and update it whenever a new event occurs (limit order submission, market order submission, limit order cancellation). When a new limit order is

¹⁴ The share of electronic trading in interbank trading is by some authors even estimated at 85% of the total interbank activity (Sager & Taylor 2006).

submitted, the order book is (re-)calculated by adding all activated limit orders to the relevant side of the book.¹⁵ When a new market order is submitted, it is verified whether the activated orders that leave the book upon submission of the order cover the market order. If not, the liquidity available for the activated limit orders at the opposite side of the book is adapted. A marketable limit order is treated in the same way as a market order, but if it has not been filled completely it will stay in the book with a reduced volume.¹⁶ Cancellation of existing limit orders is also taken into account: it is verified whether orders leave the book before the next order is submitted to the trading platform. Each time this happens, a new event is identified and added to the time series of limit order book states. The event time will here be the removal time of the order. To obtain the new order book state the post-event orders are sorted according to price and time priority.

The output of the limit order book reconstruction process is a series of observations in event-time, with for each event a timestamp at 10 ms. precision and all orders at the bid and ask side (with their respective quotes, quantities, record numbers, entering and removal times). For very short periods zero or negative spreads can be observed. Their presence can be explained by the absence of clearing agreements between certain banks (in this case, the two banks who have posted the best orders at the respective sides of the book do not have such an agreement). As other banks, which do have clearing agreements with the issuers of the best orders from both sides, can take advantage of this situation, these zero or negative spreads are short-lived.

We leave out legally recognized holidays in Hungary and weekends.¹⁷ Figure 1 shows graphically the evolution of the HUF/EUR quote and the volume traded via the electronic limit order book. Furthermore, we only use data from 7am till 7pm CET. Figure 2 shows the bimodal intraday distribution of ticks (with e.g. the quantity of ticks displayed at 5 containing all ticks between 5am till 6am). After the time filter, we still cover almost the complete market activity. Table 2 shows key characteristics of the orders submitted to the market over the sample period, split up per half-year. The type of orders is shown to be very stable over time: 15-16% of the orders are market orders, 54-60% of the orders are limit orders which are cancelled without execution and 25-30% of the orders are limit orders which are partly

¹⁵ Activated orders are the orders which have been entered before the event time, and which have not left the book at the event time. Activated orders should not be confused with active orders (i.e. orders which initiate a trade).

¹⁶ A marketable limit order is a limit order that can be immediately executed, because its price is equal to or better than the best quote from the opposite side of the book.

¹⁷ For 2003 these were: 1/01, 15/03, 21/04, 1/05, 9/06, 20/08, 23/10, 1/11, 25/12 and 26/12. For 2004 these were: 1/01, 15/03, 12/04, 1/05, 31/05, 20/08, 23/10, 1/11, 25/12 and 26/12.

matched with market orders or with marketable limit orders. This implies that only 30-35.20% of the limit orders are executed to some extent. This share is fully in line with what has been found for the GBP/ USD and the EUR/ GBP pair, for which the identical ratio was respectively 36.10% and 27.50% over 2003 and 2004 (Kozhan *et al.* 2012). Cancellations are used strategically by foreign exchange traders: they are used to display liquidity which is removed before it can be taken, but also to adapt the trader's quotes to the market environment. When we look to the order size, we find that major part (71-79%) of the orders have a size of € 1 mill., which is the minimum size. The fact that trades for the minimum size dominate is consistent with a widespread use of order splitting strategies by traders (in an attempt to minimize the market impact, see also Kyle (1985)). Table 3 presents basic descriptives of the limit order book. The quoted spread increases in the second half of 2003 (from 0.31 to 0.39 HUF/EUR) and decreases in 2004 (till 0.24 HUF/EUR). The average breadth (the quantity available at the best quote) is, interestingly, always bigger on the bid side. The same accounts for the average depth over the whole order book. In the second half of 2003 and the second half of 2004 we observe a sudden and large increase in depth at the bid side. This unusually high depth is caused by positive outliers: in the periods 24/9/2003-9/10/2003 and 10/11/2004-31/12/2004 there are unusually high orders added to the bid side (however, away from the best quote). The number of price levels at the bid side is on average 6-7. At the ask side there seems to be a slight increase in the average number of levels (from 5.64 in the first half of 2003 till 7.35 in the second half of 2004).

The advantage of our dataset for the analysis of jumps and their link with liquidity is threefold. First, on the foreign exchange market orders can be submitted on a continuous basis. There are, in contrast to for example equity markets, no opening or closing sessions that can affect the data. As the observed price and liquidity can never be driven by these artificial operations, the dynamics between announcements and liquidity should become clear more easily. Secondly, we are able to observe the complete liquidity as there are no orders which display only part of their total volume (iceberg orders). By consequence we have a clear view on the supply and demand on the market. Thirdly, we cover the lion's share of the market activity on the HUF/EUR market (most of the trading activity on the HUF/EUR market takes place via electronic limit order books, and we completely cover this form of trading). Compared to other studies, our dataset is unusually rich. This is to our knowledge the only study in which a complete tick-by-tick database and a full order book over a timespan as long as two years is used for the foreign exchange market.

3. Methodology

3.1. Jump Detection

Realized variance and Bipower variation

We assume that the log-price $p(t)$ of the underlying asset follows a continuous-time jump-diffusion process (i.e. a Brownian semimartingale with finite jump process), as is traditionally used in asset pricing (Andersen et al. 2007b; Lee & Mykland 2008; Evans 2011):

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + k(t)dq(t) \quad [3.1]$$

where $\mu(t)$ is the continuous and bounded drift term, $\sigma(t)$ a strictly positive stochastic volatility process with a sample path that is right continuous and has well defined limits, $W(t)$ a standard Brownian motion, $q(t)$ is a counting process with possible time-varying intensity $\lambda(t)$ (which implies $P[dp(t) = 1] = \lambda(t) dt$), and $k(t) \equiv p(t) - p(t-)$ is the size of the corresponding discontinuous jump in the underlying log-price movement, provided the jump exists.

Given the above theoretical setup, the quadratic variation (QV) for the cumulative return process over a fixed time interval T , consists of both, the continuous volatility component and the contribution of jumps to volatility. It is defined as:

$$[r, r]_T = \int_0^T \sigma^2(t)dt + \sum_{0 < s < T} k^2(t) \quad [3.2]$$

According to Barndorff-Nielsen and Shephard (2004), a non-parametric measure of the daily return variation, realized variance (RV), is defined as the summation of the M high frequency intra-daily squared returns within day i :

$$RV_i = \sum_{j=1}^M r_{i,j}^2 \quad [3.3]$$

where $r_{i,j}$ is the return in the interval j out of M intervals on day i .¹⁸

Based on the theory of quadratic variation (Barndorff-Nielsen & Shephard 2004, 2006a), realized variance converges to its probability limit, the increment of the quadratic variation process as the sampling frequency M tends to infinity:

¹⁸ We refer to r_i as the return on day i , and to r_{ij} as the return in interval j on day i . Therefore daily and intradaily returns are linked by $r_i = \sum_{j=1}^M r_{i,j}$, with a total of M subintervals for each day.

$$RV_i \rightarrow \int_{i-1}^i \sigma^2(t)dt + \sum_{i-1 < t \leq i} k^2(t) \quad [3.4]$$

Therefore, the realized variance is a consistent estimator of the total return variation regardless of the existence of within-day jumps.

To decompose the continuous sample path component from the QV process, Barndorff-Nielsen and Shephard (2006a) introduce the scaled realized bipower variation (BPV), defined as the summation of the product of adjacent absolute high frequency returns standardized by a constant:

$$BPV_i = \mu_1^{-2} \sum_{j=2}^M |r_{i,j}| \cdot |r_{i,j-1}| \quad [3.5]$$

where $\mu_1 = E(|u|) = \sqrt{2/\pi}$ and $u \sim N(0,1)$.

Under some further assumptions¹⁹ regarding the underlying log-price dynamics in equation [3.1], the (scaled) realized bipower variation converges uniformly in probability to the integrated volatility as M tends to infinity (for a proof see Theorem 2 in Barndorff-Nielsen and Shephard (2004)):

$$BPV_i \rightarrow \int_{i-1}^i \sigma^2(t)dt \quad [3.6]$$

Therefore, the difference between the realized variance and the (scaled) realized bipower variation provides a consistent estimation of the pure jump contribution to the quadratic variation process within the day, as M tends to infinity:

$$RV_i - BPV_i \rightarrow \sum_{i-1 < t \leq i} k^2(t) \quad [3.7]$$

Based on the relation between realized variance and bipower variation it is then possible to construct tests for the occurrence of jumps, see Huang and Tauchen (2005) for a survey. We rely on the ratio test statistics (Z) to identify statistically significant jumps (See Huang and Tauchen 2005):

¹⁹ As is further demonstrated in Barndorff-Nielsen and Shephard (2006a), the only additional assumption required is that the stochastic volatility $\sigma(t)$ is independent of the standardized Brownian motion $W(t)$ in equation [3.1]

$$Z_i = M^{\frac{1}{2}} \frac{[RV_i - BPV_i]RV_i^{-1}}{[(\mu_1^{-4} + 2\mu_1^{-2} - 5) \cdot \max\{1, TQ_i \cdot BPV_i^{-2}\}]^{\frac{1}{2}}} \sim N(0,1) \quad [3.8]$$

with the tripower quarticity (TQ) defined as

$$TQ_i = M\mu_{4/3}^{-3} \sum_{j=3}^M |r_{i,j}|^{\frac{4}{3}} \cdot |r_{i,j-1}|^{\frac{4}{3}} \cdot |r_{i,j-2}|^{\frac{4}{3}} \quad [3.9]$$

Where $\mu_{4/3} = E\left(|u|^{\frac{4}{3}}\right) = 2^{\frac{2}{3}} \Gamma\left(\frac{7}{6}\right) / \Gamma\left(\frac{1}{2}\right) \approx 0.8309$.

Under maintained assumptions, equation [3.8] implies that the ratio statistic follows standard normal distribution. Following the literature we set the significant level to $\alpha = 0.0001$ and therefore the critical value is $\Phi_{1-\alpha} = 3.719$.

Microstructure noise and jump measurements

In practice, the assumed regularity of the log-price movement is contaminated by market microstructure frictions such as discrete price tick, bid-ask spread bounce and etc. On the one hand, the existence of microstructure noise in the underlying log-price process renders realized variance an inconsistent estimator of its probability limit (the quadratic variation) (Andersen et al. 2007b). On the other hand, both the realized bipower variation and tripower quarticity are biased against the finding of significant jumps due to the noise-induced first-order autocorrelation revealed in the high frequency return series. To alleviate the adverse effect of microstructure noise on jump detection scheme, we tackle the problem in two ways: first, we choose a ten-minute sampling frequency at which the microstructure frictions no longer present a distorting influence on realized variance (Andersen et al. 2010)²⁰. Second, we modify the calculation of realized bipower variation and tripower quarticity by replacing the adjacent absolute returns in equation [3.5] and [3.9] with their staggered counterparts to break up the spurious autocorrelation pattern observed in the high frequency return series (similar to Andersen et al. (2007a); Beine et al. (2007); Evans (2011); among others):

²⁰ The volatility signature plots in Andersen *et al.* (2010) suggests that there's a systematic declining pattern in the realized variance measure as the sampling frequency increases in the range of 5 to 300 seconds, which destabilizes our measurement of RV (and hence the difference between RV and BPV), therefore, a 10-minute sampling scheme seems an appropriate, albeit somewhat conservative, method to control microstructure noise.

$$BPV_i = \mu_1^{-2} \left(\frac{M}{M-2} \right) \sum_{j=3}^M |r_{i,j}| \cdot |r_{i,j-2}| \quad [3.10]$$

$$TQ_i = M\mu_{4/3}^{-3} \left(\frac{M}{M-4} \right) \sum_{j=3}^M |r_{i,j}|^{\frac{4}{3}} \cdot |r_{i,j-2}|^{\frac{4}{3}} \cdot |r_{i,j-4}|^{\frac{4}{3}} \quad [3.11]$$

The staggered version of realized bipower variation and tripower quarticity is then used in equation [3.8] to compute the new ratio test statistic for jump detection. Huang and Tauchen (2005) show that the ratio Z-statistic with staggering offers improved size and power properties in finite sample simulation and is quite robust to the size of microstructure noise.

When the null hypothesis that there is no intraday jump is rejected based on the daily test statistic, we apply the sequential intraday jump detection scheme proposed by Andersen et al. (2010) to identify all the intraday jumps and their associated timing within the day.²¹ This sequential intraday jump detection scheme consists of several steps. If the ratio statistic (Z) is significant at day i , we first assume that only one intraday return contributes to the significant Z-stat and then proceed as follows:

Step 1: We record the significant ratio statistic Z_i and extract the series of the M intraday (geometric) returns $\{r_{i,1}, r_{i,2}, \dots, r_{i,M}\}$ within day i .

Step 2: For each intraday return $r_{i,j}$ ($j=1,2,\dots,M$) at day i , we generate a modified series $\{r_{i,1}, r_{i,2}, \dots, r_{i,mean}, \dots, r_{i,M}\}$ by replacing the j th element with the average of the remaining $M-1$ returns (denoted as $r_{i,mean}$), while keeping the rest unchanged. Then we recalculate the RV measure and its corresponding Z-stat (denoted as $Z_i^{(j)}$) with the following two formulas:

$$RV_i^{(j)} = \frac{M}{M-1} \sum_{j=1, j \neq j}^{M-1} r_{i,j}^2 \quad [3.12]$$

$$Z_i^{(j)} = M^{\frac{1}{2}} \frac{[RV_i^{(j)} - BPV_i] \cdot [RV_i^{(j)}]^{-1}}{[(\mu_1^{-4} + 2\mu_1^{-2} - 5) \cdot \max\{1, TQ_i \cdot BPV_i^{-2}\}]^{\frac{1}{2}}} \sim N(0,1) \quad [3.13]$$

²¹ Jiang and Oomen (2008) and Jiang *et al.* (2011) use a similar sequential jump identification scheme with the slight difference that they use the median of the remaining intraday returns to calculate the revised ratio statistics.

Hence, we obtain a series of M revised Z -stats $\{Z_i^{(1)}, Z_i^{(2)}, \dots, Z_i^{(M)}\}$ for the i th sample day.²²

Step 3: We calculate the differences between the original Z -stat and (each of) the new Z -stats $\{Z_i - Z_i^{(1)}, Z_i - Z_i^{(2)}, \dots, Z_i - Z_i^{(M)}\}$. The significant jump return $r_{i,J}$ is identified when the following mathematical expression achieves its maximum.

$$I_{\{Z_i > \Phi_{1-\alpha}\}} \left(\max_{J \in \{1, 2, \dots, M\}} Z_i - Z_i^{(J)} \right) \quad [3.14]$$

Step 4: We retain the revised Z -stat ($Z_i^{(J)}$) identified in Step 3. If $Z_i^{(J)}$ is less than the pre-set critical value, we conclude that there is only one jump on day i . However, if it still exceeds the critical value, we then assume that a second intraday jump exist on day i and start over again from Step 1 to Step 4 with the new geometric return series $\{r_{i,1}, r_{i,2}, \dots, r_{i,J-1}, r_{i,J+1}, \dots, r_{i,M}\}$ of $M-1$ elements.²³

The above recursive procedure continues until all the intraday jumps within day i are identified. In this way, we are able to detect all the intraday jumps throughout the 2-year sample period.

3.2. Event study methodology

Following the literature, we analyze the intraday liquidity dynamics around jumps using the intraday event study methodology in Section 5 (see Boudt & Petitjean 201x; Gomber *et al.* 2013; Mazza 2013 , for similar application). We employ a variety of liquidity measures commonly used in the empirical literature to capture the different dimensions of the market liquidity (eg. Boudt & Petitjean 201x; Mazza 2013). Appendix I gives a full-fledged definition of all the liquidity measures used in the study.

The event study approach proceeds as follows: first, we construct a centered jump event window which includes the six 10-minute intervals before and after the jump event. Second, we exclude intraday jumps which are clustered in time in order to avoid contagion effect. That is, when two jumps occur within the same day, they must be separated in time by at least two hours. Otherwise, both of the jumps are excluded from our sample. For similar concerns, days

²² Following Andersen *et al.* (2010) and Jiang *et al.* (2011), we do not change the value of BPV and TQ based on the revised intraday return series. The theoretical justification is that BPV and TQ are asymptotically robust to the existence of jump(s).

²³ More generally, after identifying n jumps ($n > 1$), we filter out the n significant jumps to obtain a new series of geometric returns with $M-n$ elements. The revised RV measure is then computed by first summing up the squared returns of the remaining $M-n$ elements, and then scaling the summation by a factor of $M/(M-n)$.

with three or more jumps are also excluded from the final sample. Third, all liquidity measures are standardized to make them comparable across days and intraday periods. Given the fact that liquidity measures are highly skewed at the intraday level and have strong seasonal patterns, we opt for the novel standardization procedure highlighted in Boudt and Petitjean (201x). Appendix II provides a detailed description on the standardization procedure. Fourth, we aggregate across individual jump events for a single point estimate. We favor the median value, rather than the mean value, of the standardized liquidity measure across individual events as our point estimator. The rationale behind our preference is well-grounded. First, liquidity measures such as number of trades, trading volume, and depth (per ten minutes) have a lower bound of zero, while in theory they do not have an upper bound. Therefore, the distribution of their standardized value remains highly skewed, which is also confirmed in our sample. Second, as argued by Boudt *et al.* (2011), the median of the standardized liquidity measures on non-jump days will be 1 for depth and volume measures and 0 for order and depth imbalance measures by construction. In that case, the interpretation of the median of the standardized liquidity measure is quite straightforward: it shows the (percentage) deviation from the typical levels during the same time of the day. Fifth, a Wilcoxon rank sum test on the median is performed to evaluate the null hypothesis that price jumps do not have any effect on liquidity. In other words, liquidity measures tend to stay at their normal level around jumps (median value of the standardized liquidity measures is zero). The alternative hypothesis is that liquidity measures are either abnormally lower or higher than their normal level around jumps.

It is important to mention that we explicitly distinguish between positive jump events and negative jumps events, as positive jumps are mostly linked with large market buy orders combined with the paucity of liquidity at the ask side while negative jumps are linked with large market sell orders combined with the paucity at the bid side. In other words, we expect the liquidity dynamics around positive jumps and negative jumps to mirror each other in the mechanical sense: what we, for example, see on the bid side during a positive jump interval should be compared with what we see on the ask side during a negative jump interval. Therefore, we distinguish in our final event study between positive jump events and negative jump events. For each category, we further divide them into positive (negative) jumps events associated with news announcements and positive (negative) jumps events without news announcements.

4. Jumps and news announcements

Prevalence and size of jumps

In this subsection, we investigate the jump intensity and magnitude for the HUF/EUR rates, which is a relatively illiquid market compared to major currencies such as USD/EUR. The results are summarized in Table 4. We detect 90 realized jump days with at least one intraday jump. There are 125 intraday jumps in total (see Table 5). The jump intensity—defined as the ratio of realized jump days to total trading days—is 18.2% for our sample period, which is quite similar to the jump frequency found in prior literature on the major currency markets: Beine *et al.* (2007) report a jump intensity of 10%–13% for the USD/EUR and JPY/USD markets between 1987 and 2004. Andersen *et al.* (2007a) document a 14% jump frequency for the DEM/ USD rates between 1986 and 1999. Lahaye *et al.* (2011) report that the jump frequency lies within the range of 22%–25% for the USD/EUR, USD/GBP, USD/JPY and USD/CHF markets between 1987 and 2004. We further find that the average time length between two jump days (in the literature mostly referred to as the “jump duration”) is 6.6 days. We also calculate to what extent the jump component contributes to the realized variance on realized jump days. On average, 42.59% of the price variation on jump days can be attributed to jumps. This is also in line with previous work on major currencies. For example, Evans (2011) report a jump contribution of 35.80% on the the USD/ EUR market.

When comparing positive and negative jumps (see Table 5), we find that the differences both in terms of frequency and magnitude are small and not statistically significant. Therefore, we can conclude that jumps are symmetric in terms of both frequency and size. This is consistent with previous research on major currency markets (Lahaye *et al.* 2011).

We find that intraday jumps are concentrated on two periods, one in the morning (between 8:00 and 8:20 (CET)) and one in the afternoon (between 15:50 and 16:50 (CET)). We see that 66.67% of the jumps takes place during these timespans.

*Jumps and public news announcements*²⁴

By theory, price tends to jump to the new equilibrium level immediately after new information (shocks) has been revealed to the market. Therefore, one obvious source of jumps is prescheduled macroeconomic news. These announcements represent potential shocks to the market if the statistics released do not match the market expectations.²⁵ Previous research in

²⁴ The data on news announcements is collected from the Dow Jones Factiva database, which contains all the historical (news) data from the leading newswires such as Reuters and Dow Jones newswires.

²⁵ Unfortunately, we cannot observe the surprise component of the announcement.

this field suggests that nonfarm payroll, central bank announcements, and trade balance shocks are the major news items that are most closely linked with foreign exchange jumps (Neely 2011). In this work, we also adopt a variety of macro news items such as the releases of GDP, PPI and trade balance information in Hungary and the European Union. To account for possible cross-currency pressure such as cojumps and global liquidity shocks (see Banti *et al.* 2012), we also include the macroeconomic announcements from the United States, leading EU countries such as Germany and France, and neighbouring CEEC countries such as Poland.^{26, 27} Following Lahaye *et al.* (2011), we attribute the jump occurrence to a news event using a 60-minute matching window centered around the jump. That is, if a news event takes place between the 30 minutes before and 30 minutes after the jump interval, we assume that the jump is directly linked with it. Table 6 summarizes our findings for the 125 intraday jumps we identified. We can link 16% of the detected jumps with scheduled news announcements. The conditional probability of observing a jump given a particular sort of news item is the highest for GDP releases for Hungary (25%), followed by inflation releases for Germany (8.33%) and inflation releases for Poland (8.33%). Given a jump, there is no clear pattern as which type of news has a high probability of having caused the jump (not a single type of news has a higher conditional probability than 1.60%).

In addition to linking jumps with prescheduled macroeconomic announcements, we also investigate the linkage between unscheduled news announcements and the jumps. The theoretical justification behind is that real-time news reports also influence market participants' expectation on the fundamentals regarding the exchange rates. A more detailed illustration on the theoretical underpinning of the exchange rate determination is given in (Evans & Lyons 2005). Following Copeland (2005), we restrict the potentially relevant, unscheduled news items to one of the following categories of news reports: 1) central bank interventions, 2) polls, surveys, forecasts, analyses by financial institutions and leading economists, and 3) political changes and/or natural disasters. Table 7 presents our results in

²⁶ The motivation for incorporating macroeconomic announcements for other economies is two-folded. First, market participants form their expectations on macroeconomic statistics for the European Union based on the release of national statistics, which takes place earlier than the release of the aggregated statistics. Secondly, recent empirical evidence on cojumps on foreign exchange markets showed that fundamental shocks to one currency pair can put substantial risk on linked markets (Lahaye *et al.* 2011; Neely 2011).

²⁷ Our list of the prescheduled macroeconomic news items is comprehensive. We include CPI, GDP, current account balance, public sector balance, MPC meetings-base rate decisions, retail sales for Hungary; PPI, CPI, GDP, unemployment rate, retail trade, industrial production, current account balance, public sector balance, external trades, labor costs, M3 for EU, Germany and CEEC countries (if available); PPI, CPI, non-farm payroll, GDP advance, GDP preliminary, GDP final, trade balance, industrial production, unemployment rate, consumer confidence, new home sales, construction spending, ISM index for the US. Contrary to the conventional wisdom, US non-farm payroll, GDP releases and unemployment rates do not cause any jumps during our sample periods.

detail. We can link a significant part of the jumps (30.4%) with unscheduled news announcements. Amongst the 15 largest jumps, 4 jumps can be explained by this type of news (as much as the number of jumps that can be explained by scheduled macroeconomic news announcements). Overall, our results suggest that unscheduled, real-time news is another important source of jumps. Still, nearly half of the jumps remain unexplained, which is possibly due to the prevalence of private information in the FX market. Informed traders capitalize on their private information by taking up the liquidity of the order book, forcing the price to jump to a new level. Section 5 and 6 provide more in-depth evidence on our conjectures of informed trading by examining the liquidity dynamics around the jump.

5. Jumps and liquidity dynamics

In addition to investigating the link between public news and jumps, a proper understanding of jumps and where they come from requires an in-depth analysis of the interaction that takes place in the book around jumps. Conventional wisdom suggests that a jump reflects the inability of the limit order book to absorb relatively large market orders quickly. Therefore, large market orders have to walk up or down the book for execution. However, this mechanical view neglects the role of limit order flows when a jump occurs. In fact, the limit order book is a platform where interaction, among informed traders, market makers (liquidity providers) and noise traders, takes place via market and limit orders. The sudden increase of volatility impacts the liquidity of the market as traders (dynamically) revise their order placement strategy (such as order aggressiveness and order size). Therefore, built on theoretical models of the limit order book developed in previous research (Glosten 1994; Foucault 1999), we further develop hypotheses on the dynamic relation between price jumps and the different dimensions of liquidity.²⁸ We compare our findings with results for Dow Jones stocks, and these are currently the only other results for this type of analysis.

In this section we describe the liquidity dynamics prior to, during and after jumps, incorporating both the mechanical and dynamical view (as they both can matter). The findings in this section shed a new light on what the cause is of jumps, whether there is a stylized liquidity pattern that precedes jumps and how the jump affects the interaction that takes place. We apply here the event study approach (cf. *supra*). We are concerned about potential

²⁸ Here we use a broader definition of news, which includes now also private news such as the customer order flow observed by the market participant. The assumption that jumps are information-based is supported by the fact that we observe an increased imbalance of the order flow during jumps, which is a common proxy for information. Additional evidence can be found in the price reversal pattern after the jump (See Figure 4)

contagion between individual jumps, and therefore exclude jumps which are clustered. After the filtering procedure (cf. supra), 80 intraday jumps remain in our sample. These jumps will be used for the liquidity analysis. For clarification purpose, we present here mainly the liquidity dynamics around positive jumps as the liquidity dynamics around positive jumps and negative jumps mirror each other.²⁹ The detailed results can be found in Table 8 (positive jumps) and Table 9 (negative jumps).

Figure 5 till Figure 13 present boxplots for various indicators on the state of the limit order book (and this for each 10 minute interval from 1 hour prior to the jump till 1 hour after the jump). The central mark is the median, and the edges of the box are the 25th and 75th percentiles. The whiskers point at the most extreme observation which is still no outlier.³⁰

5.1 Liquidity dynamics prior to the jumps

Hypotheses: origin of jumps

Previous literature suggests that lagged liquidity shocks in the order book such as a widened spread, decreased market depth and levered number of trades indicate the occurrence of jumps (Boudt & Petitjean 201x; Jiang *et al.* 2011). Our event study setting provides a straightforward way to validate the above predictions. In case there are pre-jump liquidity shocks, we should observe the median value of some liquidity variable during the pre-jump periods to be significantly different from zero. We distinguish three potential relations between preceding liquidity in the book and the occurrence of jumps:

H1: A price jump will occur when the liquidity in the limit order book is unusually low, and cannot absorb a normal market order flow.

H2: A price jump will occur when the liquidity in the limit order book is normal, and the market order flow is unusually high.

H3: A price jump will occur when a high level of liquidity triggers an even higher flow of market orders which cannot be absorbed by the liquidity in the limit order book.

²⁹ And where this is not the case, we mention it explicitly.

³⁰ Observations are considered to be outliers if they are larger than $q_3 + 1.5*(q_3 - q_1)$ or smaller than $q_1 - 1.5*(q_3 - q_1)$ with q_1 is the 25th percentile and q_3 is the 75th percentile.

Results

Prior to a positive jump, there is no significant change in the size-weighted proportional quoted spread (tightness).³¹ Nor do we observe any strong trend in trading activities during the 60 minutes prior to the jump, as trading volume stays at its normal level and transaction order flow is balanced (immediacy). Furthermore, the volume of outstanding limit orders (both overall and at the best quote) on the side that has to absorb the jump shows no universal pattern in the 60 minutes prior to the jump (depth and breadth). This supports H2. Our findings have implications for the predictability of jumps based on the liquidity in the book, a topic that we explore further (See: 6.1 Predictability of jumps using probit analysis).

5.2 Liquidity dynamics during and after the jump

Hypotheses: interaction during jumps

In order to interpret our observations during and after the jump, we introduce here three types of participants, who follow each different order placement strategies (if any). Participants can at each point of time be classified according to the strategy they are following. Especially on this type of interbank market, the same agent can apply different strategies depending on his specific situation at that time.³² We formulate ex ante predictions on the overall outcome of a dynamic order placement strategy by these heterogeneous agents.

We distinguish respectively:

- *Informed traders*: Participants who act on private information on the future evolution of an asset, like they are introduced in Kyle (1985). On the foreign exchange market, their information can be based on the customer order flow (Rime 2000). Informed traders can be patient (and submit aggressive limit orders) or impatient (and submit market orders). The motivation for informed traders to be patient includes lower price impact.³³ They will, however, be impatient when their information is short-lived, or, following Bloomfield *et al.* (2005), when their private valuation lies outside the range of the inside quotes. Both patient and impatient informed traders can be present at the same time on the market, because they can have heterogeneous private beliefs.

³¹ We rely on the size-weighted spread, as this measure overweights (underweights) firm (non-firm) quotes.

³² In that sense, trader identities would here not be very informative.

³³ Evidence for the existence of patient informed traders can be found in, amongst others, Eisler *et al.* (2011) and Hautsch and Huang (2012). In these works it is shown that limit orders contain information, as they have a permanent price impact.

H4: The presence of patient informed traders will, upon arrival of positive (negative) information, lead to increased submission of limit orders at the buy (sell) side, against competitive quotes.

H5: The presence of impatient informed traders will, upon arrival of positive (negative) information, lead to increased submission of market buy (sell) orders.

- *Market makers:* Participants who primarily provide liquidity to the market. Although there are no designated market makers on the interbank foreign exchange market, participants can be attracted by the profit market making offers. The idea that a market making role emerges from the trading process is also referred to as endogenous liquidity provision.³⁴ Market makers set a spread between the best buy and best sell. This is the source of their revenues. When setting the spread, they take the following costs into account: order processing costs (representing per unit administration costs and fixed costs such as wages, floor space rent,...), inventory holding costs (the cost of holding an unwanted inventory) and adverse selection costs (a compensation for the risk of trading with a better informed counterparty).³⁵ They will typically submit competitive limit orders. After a jump, which we found to be trade induced in the previous paragraph, the spread rises in a limit order book because the market orders are highly imbalanced and one side of the market gets depleted. Market makers are attracted by this high spread and post limit orders.³⁶ This increase in supply of liquidity will improve the best prices, and will bring the spread back to its equilibrium value (eg. Goettler *et al.* 2005).

H6: The presence of market makers will, upon arrival of information, lead to an increased provision of liquidity at the market.

- *Noise traders:* Participants who do not trade based on information, but trade based on their liquidity needs. Their part of the flow is balanced over time. We do not observe noise traders in our results, as we only measure unexpected trading flows and unexpected liquidity.

³⁴ For a recent work dealing with the behaviour of endogenous liquidity providers in comparison to designated market makers, see Anand and Venkataraman (2013).

³⁵ For an analysis of the importance of these components on this market, see Frömmel and Van Gysegem (2012).

³⁶ As a consequence of this increased liquidity provision, the market enters then again a phase of high liquidity (which will afterwards again be taken away). This sequence of high liquidity – low liquidity is also referred to as a liquidity cycle (See e.g. Foucault *et al.* 2013) .

Results: tightness

As jumps appear to be trade-induced, the trading volume increases during a jump interval. The higher number of transactions consumes the liquidity available in the market, and the spread will consequently in a mechanical way go up. Moreover, liquidity providers tend to place limit order further away from the midquote, to avoid being picked off due to the increased price risk. However, the widening of the spread in combination with the paucity of liquidity at one side of book makes it more rewarding to provide liquidity. Discretionary liquidity providers see which side of book requires liquidity and will submit more limit orders to this side. These limit orders are designed to benefit from the increased demand for immediacy.

This is also what we observe. During the jump, the spread increases with 25.09%. We see that liquidity providers are attracted by this spread, and bring it back to its normal level 20 minutes after the jump (H6). The spread returns slightly quicker to its normal level after negative jumps.

Results: immediacy

Previous theoretical work predicts that order submissions tend to be clustered over time (amongst others, Kyle 1985; Admati & Pfleiderer 1988; Wang 1994). These findings were empirically confirmed by amongst others Campbell *et al.* (1993) and Covrig and Ng (2004). One could expect that by consequence an increase in volume traded will persist for some time after the jump. However, as spreads remain high after a jump, transactions are more costly. This high spread will impact traders submitting less aggressive limit orders.

During a jump, market order submissions in the direction of the information increase drastically. As a result, the order flow gets more asymmetrical (with an increase of the imbalance with 57.89% towards more buy orders), and the trading volume increases by 180%. (H2, H5)

The increased trading activity continues up till 20 minutes after the jump, but there is no sign of order flow imbalance ex post positive jumps. Thus, it seems like the increased trading after the jump is more balanced. The increase in trading activity is smaller after negative jumps, and the activity also returns faster to its normal level.

Results: depth and breadth

Mechanically, one would expect that the depth and breadth become unusually low at one side of the book during a jump, because informed traders are using the liquidity in one side of

the book. Within the framework of a dynamic limit order market, like it was developed by Foucault (1999) and Foucault *et al.* (2005), the increase of price risk caused by increased volatility is due to an increase in the information asymmetry across traders. Consequently, we expect an increase in the placement of limit orders relative to market orders (and thus an increase in depth) immediately after the jump. Patient traders would then make the book thicker at the opposite side. At the same time, the liquidity provision by market makers could restore the liquidity after the jump.

This is also what we see in the data. At the ask side we find that the depth decreases with 23.04%, due to the increased arrival of one-sided market orders (H5). At the same time, the total depth at the bid side is found to be 10.76% higher than expected. The liquidity at the best buy (breadth) is 14.82% higher than expected. This confirms the presence of patient informed traders (H4).³⁷ The breadth at the ask side is unusually high during the jump (8.07% higher), which is consistent with the prediction that market makers become active and start providing liquidity (H6).

Results resiliency

Using evidence from experimental asset markets, it was shown that a market making role emerges endogenously on a financial market (Bloomfield *et al.* 2005). This is in line with empirical evidence by Ahn *et al.* (2001), who highlight the importance of distinguishing between increased volatility arising from the bid side or from the ask side. Attracted by the increasing reward, traders will start to submit limit orders (and thus provide liquidity) at the side where liquidity is needed the most.

We do find in our results that the liquidity is restored after a jump, consistent with the emergence of market makers who add liquidity to the book. We see that the overall volume of limit sell orders entered after a positive jump is 127.27% higher than expected (See Table 12).³⁸ This is only partly the result of a quote updating process (as the cancellations at this side are only 86.87% higher than expected, unreported). While during the jump interval, the increased activity of patient informed traders dominates over the increase in limit orders posted by market makers, this reverts in the interval immediately after the jump. After the jump, market makers continue to provide unusually high liquidity up till 30 minutes after the

³⁷ For negative jumps, these patient informed traders seem to be active already before the jump. They post limit orders at the ask side in the 60 minutes before the jump and make the book unusually imbalanced. Their impact on the book is also bigger (respectively 22.46% and 24.11% more liquidity during and immediately after the jump compared to 10.76% and 16.50% after positive jumps).

³⁸ Later in this paper, we provide further evidence on order submission strategies (See p. 25, Post-jump order submission strategy).

jump. They bring the spread back to its normal level, and also restore the depth (from 20 minutes after the jump onwards).³⁹ Our findings illustrate the effectiveness of endogenous liquidity providers, even in a relative illiquid market and after a large price discontinuity.

Results: asymmetries between public and private news induced jumps

We find that for most liquidity dimensions, the dynamics of liquidity are very similar for jumps that are caused by public news announcements, and jumps for which this is not the case. A reason for this surprising symmetry could be that they are both linked with information, like we have argued above, and that they are in this sense also more similar than what one would expect. In Figure 4 we present the price reversal pattern, showing the median logarithmic return during the first two hours after the jump. We performed a Wilcoxon rank sum test on this return, and a star indicates that the return is statistically significant at the 5% level.

We find however one interesting and strong asymmetry in tightness: for jumps that can be linked with public news, the spread rises with 49.90% during a positive jump interval and 35.15% during a negative jump interval. For jumps that cannot be linked with public news, the spread rises only with respectively 18.52% and 17.75%. This may seem counterintuitive at first sight, because public information is symmetric and private information is not. We think this can be explained by the behavior of the liquidity providers, who are more reluctant to provide liquidity when a jump is caused by a public news announcement. It might be that they want to wait till consensus is reached on the interpretation of the news, and that they hesitate to provide liquidity when they know for sure that the movements are caused by information (even when this information is public). We find support for this in the price reversal pattern: the initial jump at both sides is reverted after public news announcements, while this is only to a much lesser extent the case for jumps that are not linked with a public news announcement. This also points at an insufficient liquidity provision in an early stage after the jump.

6. Further Analysis

The prior section provides a comprehensive view on how market liquidity evolves around the jump. However, several important issues remain unsolved: is it possible to forecast the jump occurrence using information available prior to the jump? Does the speed of price discovery remain unchanged after the jump? What kind of order placement strategy do traders

³⁹ After positive jumps, the depth and breadth become even unusually high till 40 minutes after the jump. This overshooting cannot be found back after negative jumps.

adopt after experiencing the extreme price risk due to jumps? In this section we provide further evidence on these issues.

6.1 Predictability of jumps using probit analysis

Despite the fact that we find only a very weak, if any, pre-jump liquidity pattern in the event study section, it is still possible that a certain dimension of the liquidity shocks is indicative of subsequent jumps, or multiple dimensions of the liquidity shocks jointly contribute to the occurrence and/or the magnitude of jumps. To formalize the linkage between jumps and liquidity shocks, we follow the literature by modelling intraday jumps as a non-linear function of liquidity shocks and news surprises (Boudt & Petitjean 201x; Jiang *et al.* 2011; Lahaye *et al.* 2011). To assess the predictive power of liquidity shocks prior to the jumps, we focus on all the single jump days and perform a probit regression as in Jiang *et al.* (2011). The restriction to days with only one intraday jump is necessary to avoid the contagion effect from consecutive jumps in the same day, which is common in the literature (Boudt & Petitjean 201x; Jiang *et al.* 2011). The explanatory variables in our probit regression are selected in an attempt to cover all dimensions of liquidity and are in line with Boudt and Petitjean (201x). The model specification of the probit regression looks as follows:

$$P(JUMP_t = 1|\mathbf{Z}) = \Phi \left(\begin{array}{l} \alpha + \beta_1 SWPQS_{t-1} + \beta_2 Volume_{t-1} + \beta_3 |OI|_{t-1} + \beta_4 MD_{t-1} \\ + \beta_5 |DI|_{t-1} + \gamma INFO_t + \varepsilon_t \end{array} \right) \quad [6.1]$$

where $P(JUMP_t = 1|\mathbf{Z})$ denotes the probability that a jump occurs conditional on a set of explanatory variables, \mathbf{Z} .

In equation [6.1], the set of explanatory variables includes lagged values of spread ($SWPQS$), trading volume ($Volume$), absolute order flow imbalance ($|OI|$), mean depth at the best price (MD) and absolute depth imbalance ($|DI|$) at the best price. In addition, a contemporaneous informational dummy ($INFO$) is also added to control for the possible announcement effect. The *iid* error term is denoted as ε . All the liquidity variables used in [6.1] can be inferred from the Reuters screen, which is available to all market participants.

The estimation results⁴⁰ are reported in Panel A of Table 10. Consistent with our findings in the event study section, conventional liquidity measures offer weak, if any, predictive power in forecasting the occurrence of jumps after controlling the effect of informational

⁴⁰ Here we used maximum likelihood estimation.

shocks. First, none of the liquidity variables in equation [6.1] are statistically significant.⁴¹ Second, the null hypothesis that the coefficients of all liquidity variables are jointly zero is not rejected at the 10% significance level.^{42,43}

Although the results show that overall liquidity or a specific liquidity dimension do not predict the occurrence of a jump, it is still possible that liquidity can predict the magnitude of it. Therefore, in the next step, we evaluate the impact of liquidity shocks on the magnitude of the jump with a Tobit regression. The Tobit model can be seen as a truncated regression that determines the magnitude of the jump, given there is a price jump. The model specification is given as follows.

$$|JUMP_t| = \begin{cases} JUMP_t^* & \text{if } JUMP_t^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad [6.2]$$

$$JUMP_t^* = \alpha + \beta_1 SWPQS_{t-1} + \beta_2 Volume_{t-1} + \beta_3 |OI|_{t-1} + \beta_4 MD_{t-1} + \beta_5 |DI|_{t-1} + \gamma INFO_t + \varepsilon_t$$

where $|JUMP_t|$ denotes the magnitude of the observed jumps and is measured as the absolute value of the logarithmic return during the 10-minute interval. $JUMP_t^*$ denotes the latent jump magnitude. $|JUMP_t|$ equals $JUMP_t^*$ if $JUMP_t^* > 0$ and is 0 otherwise. It further assumes that there exists a linear dependence between the latent jump magnitude and all the regression variables (which are the liquidity shocks and the information dummy). The regressors are defined identically as for Equation [6.1].

Panel B of Table 10 presents the result for the Tobit regression. None of the liquidity variables are significant at the 10% level, nor do they have the expected sign. The informational dummy, however, is significant and explains the magnitude of the jump: when the jump is caused by a public news announcement, it is on average bigger.

In sum, we find little evidence that liquidity shocks predict the occurrence of jumps or explain the magnitude of jumps in our sample after controlling the effect of news announcement. This contradicts with the findings by Jiang et al. (2011) and Boudt and Petitjean (201x).

⁴¹ Here we used a (robust) t-test with Newey-West correction.

⁴² Here we used an F-test.

⁴³ Our results remain unchanged when we use a logit regression. These results are available upon request.

6.2 Post-jump price discovery

In this subsection, we further examine the price discovery process after a jump in the FX market. We here follow the methodology used in Evans and Lyons (2002). Prior evidence suggests that the informational role of transaction order flow weakens subsequent to price jumps in the US bond and equity market (Boudt & Petitjean 201x; Jiang *et al.* 2011). We extend the work on post-jump price discovery to the FX market by examining all the single-jump days and non-jump days via the following model:

$$R_{t+1} = \alpha_0 + \alpha_1 D_{JUMP} + \beta_0 OF_t + \beta_1 OF_{t+1} + \beta_2 OF_{t+1} \times D_{JUMP} + \varepsilon_{t+1} \quad [6.3]$$

where R_{t+1} denotes 100 times the change of the logarithmic mid-quote during the 10-minute interval $t+1$, OF_t (OF_{t+1}) is the signed volume of transaction order flow over the interval t ($t+1$) measured in millions of euros. D_{JUMP} is the post-jump dummy, which takes the value of one for the six 10-minute intervals immediately after the jump and zero otherwise.

We differ from previous studies such as Jiang *et al.* (2011) by including the lagged order flow (OF_t) in the model specification to account for the possible price reversal in the next period as suggested by Pástor and Stambaugh (2003). That is, we expect that both the lagged and current order flow would impact price discovery process, but in the opposite direction. Therefore, the coefficient β_0 captures the liquidity effect of lagged order flow, β_1 captures the normal price impact of order flow, and β_2 captures the additional price impact of contemporaneous order flow immediately after the jump, which is robust to subsequent price reversals.

The results of the regression are presented in Table 11.⁴⁴ The coefficient on contemporaneous order flow is significantly positive, confirming the role of order flow in the price discovery process (see Evans & Lyons 2002). As expected, the coefficient on the lagged order flow is significantly negative but much less in magnitude than that on the current order flow, suggesting the existence of subsequent price reversal due to illiquidity. Finally, the coefficient on the interaction term between the post-jump dummy and the current order flow is significantly negative at the 5% level. This is consistent with prior literature that the informational role of post-jump order flow is less pronounced than during normal trading periods.

⁴⁴ We used Ordinary Least Squares regression to obtain these results. The t-statistics are Newey-West corrected.

While we confirm the stylized fact regarding post-jump price discovery, it remains interesting to investigate why order flow becomes less informative immediately after jumps. Jiang *et al.* (2011) attribute it to the possibly lowered dispersion of investor belief immediately following the occurrence of jumps. Motivated by our findings in the event study, we, however, perceive it differently: the reduced informational role of (transaction) order flow may as well be explained by the altered order submission strategy immediately after the price jump, which we investigate in the next subsection.

6.3 Post-jump order submission strategy

In this subsection, we investigate in depth the impact of jumps on the subsequent order placement strategy using regression analysis. Prior studies suggest that a higher proportion of limit orders relative to market orders emerges immediately after enlarged asset volatility or a widened spread (Biais *et al.* 1995; Griffiths *et al.* 2000; Ahn *et al.* 2001; Cao *et al.* 2008). Motivated by our findings in the event study section, we extend the order placement literature by focusing on the impact of intraday jumps, rather than volatility, on the subsequent order-flow composition. In particular, we estimate whether the occurrence of jumps leads investors to submit more limit orders relative to market orders, or the other way around.

To address these questions, we use the change of market depth available at the best price from interval t to $t+1$ ($\Delta Depth_{t+1}$) as a proxy of the order-flow composition. As it is argued by Ahn *et al.* (2001), $\Delta Depth_{t+1}$ captures the difference between the net volume of newly placed limit orders and the volume of market orders executed during the time interval $t+1$. Therefore, we estimate the following empirical model which is similar to Equation 6 in Ahn *et al.* (2001).

$$\begin{aligned} \Delta Depth_{t+1} = & \alpha_0 + \alpha_1 D_{JUMP} + \rho_1 \Delta Depth_t + \beta_0 Risk_t + \beta_1 Risk_t D_{JUMP} + \\ & \sum_k \gamma_k TIME_{k,t+1} + \varepsilon_{t+1} \end{aligned} \quad [6.4]$$

where $\Delta Depth_{t+1}$ ($\Delta Depth_t$) is the change of mean depth available at the best price from interval t ($t-1$) to $t+1$ (t), D_{JUMP} is the post-jump dummy, which takes the value of one for the six 10-minute intervals immediately after the jump and zero otherwise, $Risk_t$ is the volatility risk (measured as the square of the intraday return) during the interval t , $TIME_{k,t+1}$ is an intraday dummy variable that takes the value of one if interval $t+1$ belongs to the time interval k and zero otherwise, and ε_{t+1} is the *iid* error term.

Apparently, the coefficient ρ_1 measures the autocorrelation pattern of the change of market depth, while γ_k controls for the typical intraday variation in liquidity variables (“time of day” effect). The coefficient β_0 measures the effect of increased volatility on the subsequent order-flow mix and β_1 captures the additional post-jump impact on order-flow composition, which is of our interest.

The result of the regression is presented in Table 13.⁴⁵ For the purpose of brevity, we only report the coefficients on the lagged changes of market depth, lagged volatility risk, the post-jump dummy and the interaction term. Consistent with prior literature (see Ahn *et al.* 2001, among others), the coefficient on the lagged change of mean depth is significantly negative, supporting the self-adjusting mechanism of the order flow. That is, there will be an influx of more limit orders than market orders when limit orders were relatively scarce in the prior period, which is consistent with the conventional wisdom that market depth tends to get replenished to its normal shape (resiliency). Similar to the results reported in Table III of Ahn *et al.* (2001), there is no strong evidence that increased transitory volatility would lead investors to submit more limit orders than market orders as β_0 is insignificantly different from zero (the sign of the coefficient is in fact slightly negative).⁴⁶ Finally, the coefficient estimate on the interaction term between post-jump dummy and lagged volatility risk remains strongly positive at the 5% level, confirming our expectation that investors prefer to submit more limit orders instead of market orders subsequent to the occurrence of jumps. It should be noted that two forces contribute to the increased use of limit orders after a jump. On the one hand, the sudden increase of transitory volatility due to jumps makes it attractive for participants to adopt market making strategies, as the expected gain of supplying liquidity outweighs the expected loss of trading against an informed trader and holding an unwanted inventory for a short time span. On the other hand, even informed traders will opt for limit orders instead of market orders, because the cost of submitting a market order increases dramatically due to the rise in transitory volatility associated with the jump. As we do not have the identity of the traders, we cannot distinguish between these two forces.

Overall, our evidence on traders’ post-jump order submission strategy is consistent with the results in the event study section: the “make or take” decision is altered following price jumps as more liquidity (depth) is built up in the book with newly submitted limit orders. The

⁴⁵ We used Ordinary Least Squares regression to obtain these results. The t-statistics are Newey-West corrected.

⁴⁶ One possible explanation for the insignificance of β_0 is that the relation between transitory volatility risk and the change of market depth does not need to be monotonically increasing, nor linear. In an unreported regression we find that the coefficient on the quadratic risk is highly significant and positive, indicating the relation might not be linear.

reason for a weakened post-jump price discovery process become clear: transaction order flow become less informative with a thick order book.

7. Conclusion

Using a unique dataset (including the complete limit order book) over a two year timespan, we investigated the relation between intraday jumps, news announcements and liquidity dynamics in the HUF/EUR interdealer market.

First, our results conform to the general finding that jumps are frequent on financial markets. In a relatively illiquid FX market, such as our HUF/EUR market, we find that around 18.2% of the sample days contain at least one intraday jump with the jump component contributing to nearly one-half of the realized volatility during the jump day.

Secondly, we investigate the relation between jumps and news releases of various sorts. In particular, we employ a much broader dataset of news announcements which includes not only scheduled news releases, but also unscheduled news announcements such as polls, surveys, forecasts and analyses on future fundamentals. We find that scheduled news explains 16% of the jumps, while unscheduled news explains 30.4% of the jumps, confirming that both news on fundamentals (scheduled news), and news which will change the market expectations on future fundamentals (unscheduled news) are both important sources of large exchange rate movements. Still nearly half of the jumps remain unexplained by (public) news announcements. However, we show that jumps are information-based, independent whether they are linked with public news or not, as they have a similarly large permanent price impact and are both accompanied by highly imbalanced order flows.

Thirdly, we test the predictions from limit order book models under extreme market conditions by zooming in on the dynamics of various liquidity dimensions around jumps. Using an event-study approach, we find that prior to jumps the liquidity pattern does not deviate from that in normal trading periods. During the jump period, our results suggest that jumps do not emerge because of unusually low liquidity supply, but because of an unusually high demand for immediacy concentrated on one side of the order book. Moreover, a dynamic order placement process emerges after the jump: more limit sell (buy) orders are added to the book subsequent to a positive (negative) jump, which is consistent with the presence of endogenous liquidity providers on the market. Attracted by the higher reward for providing liquidity, they submit limit orders at the side where it is needed the most. In addition, we detect a high level of resilience in the market, but this resilience is on average more

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pronounced for negative jumps than for positive jumps. Another interesting asymmetry is that the liquidity providers tend to be more reluctant to add liquidity when confronted with a news announcement around the jump. By consequence the spreads increase more dramatically in cases of jumps with news announcements than that of jumps without news events.

Finally, our further analyses offer more insights. First, the probit analysis shows that none of the liquidity variables offer predictive power for jump occurrence, which is consistent with the normal liquidity pattern prior to jumps documented in the event study section. Second, we find that post-jump order flow is in general less informative than in normal trading periods. This is in line with the additional evidence from the third analysis on order submission strategy: more limit orders relative to market orders are submitted to the book after the jump. Therefore, the informational role of order flow becomes less pronounced in the thick order book after the jump.

One direction for future research is to investigate the liquidity dynamics around jumps under different market microstructures (e.g. market with designated market makers, the customer FX market). This would be highly relevant for the purpose of optimal market design.

FIGURES

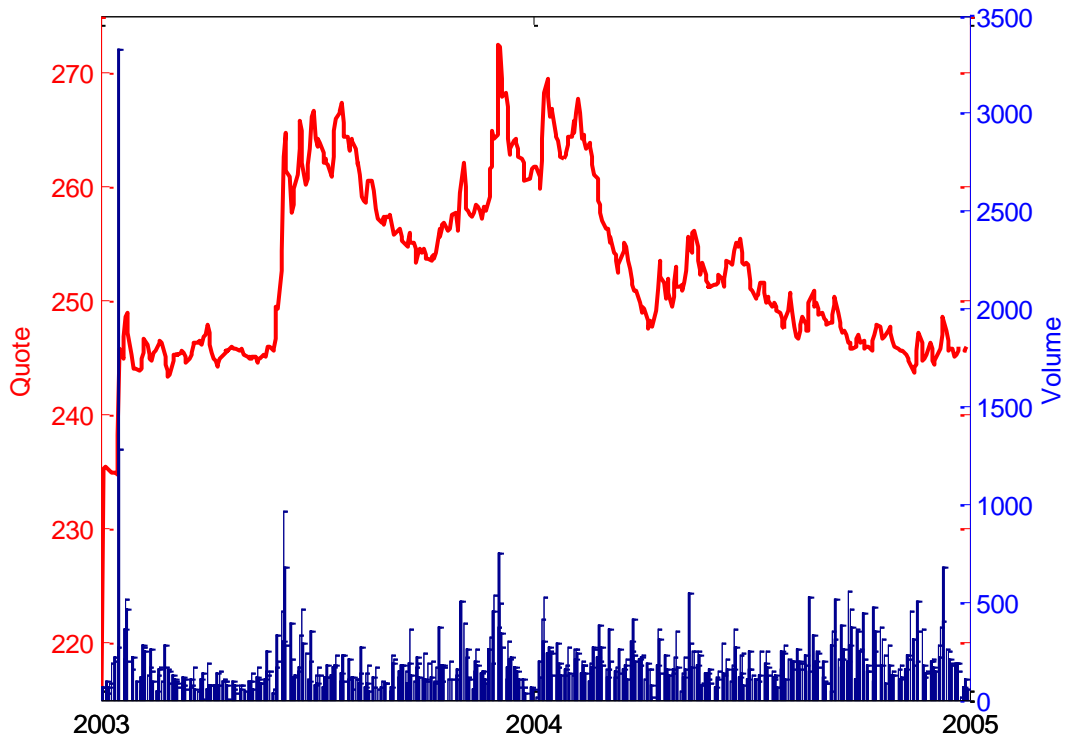


Figure 1: Average daily quote and total volume traded over the sample period.

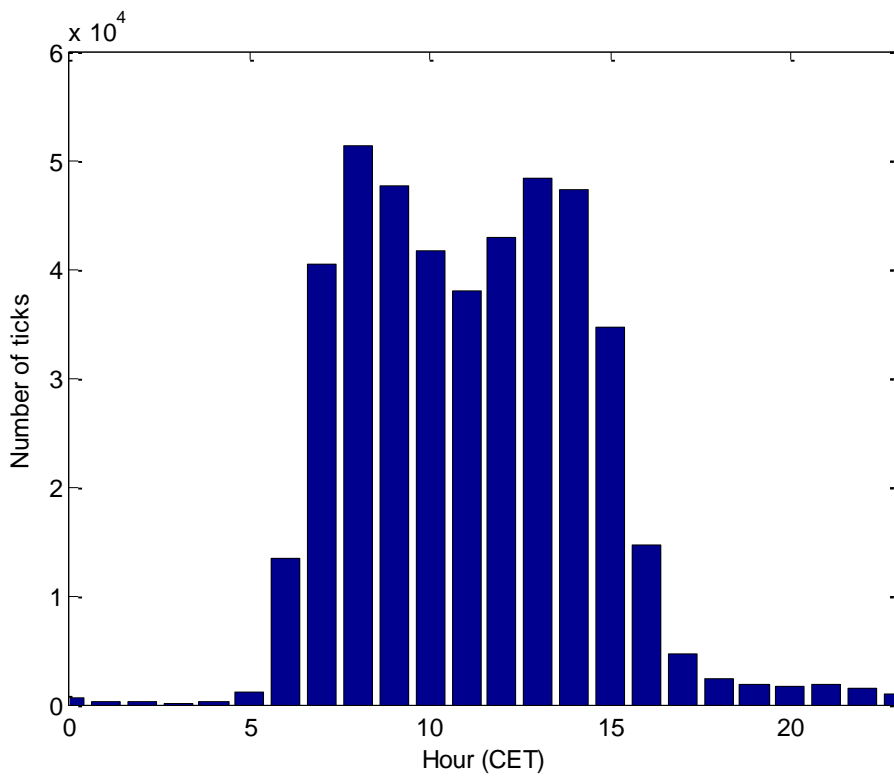


Figure 2: Intraday distribution of ticks (CET).

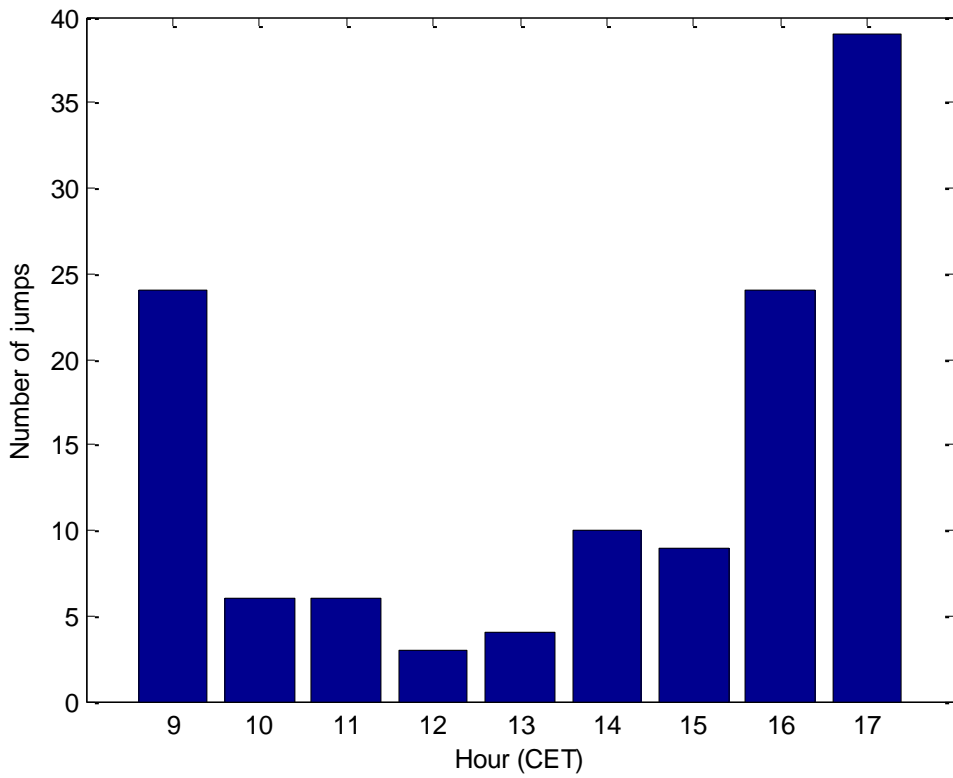


Figure 3: Intraday distribution of jumps.

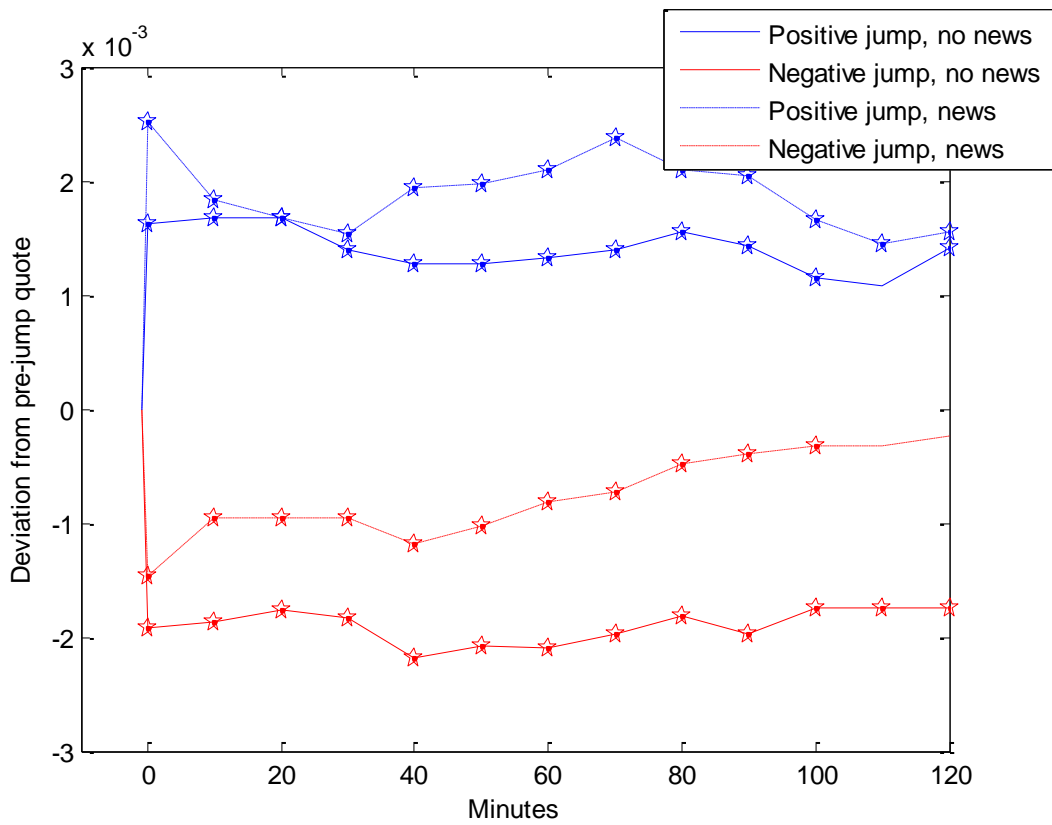


Figure 4: Price reversal after a jump (a star indicates significance at the 5% level).

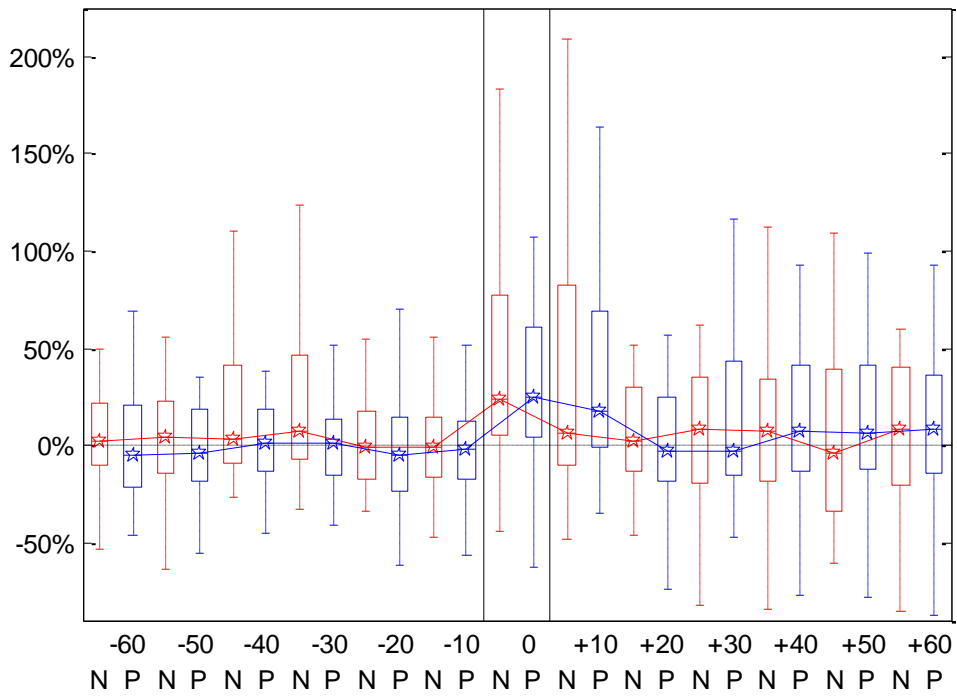


Figure 5: Bid-ask spread (SWPQS) for neg. (N)/ pos. (P) jumps during the event window.

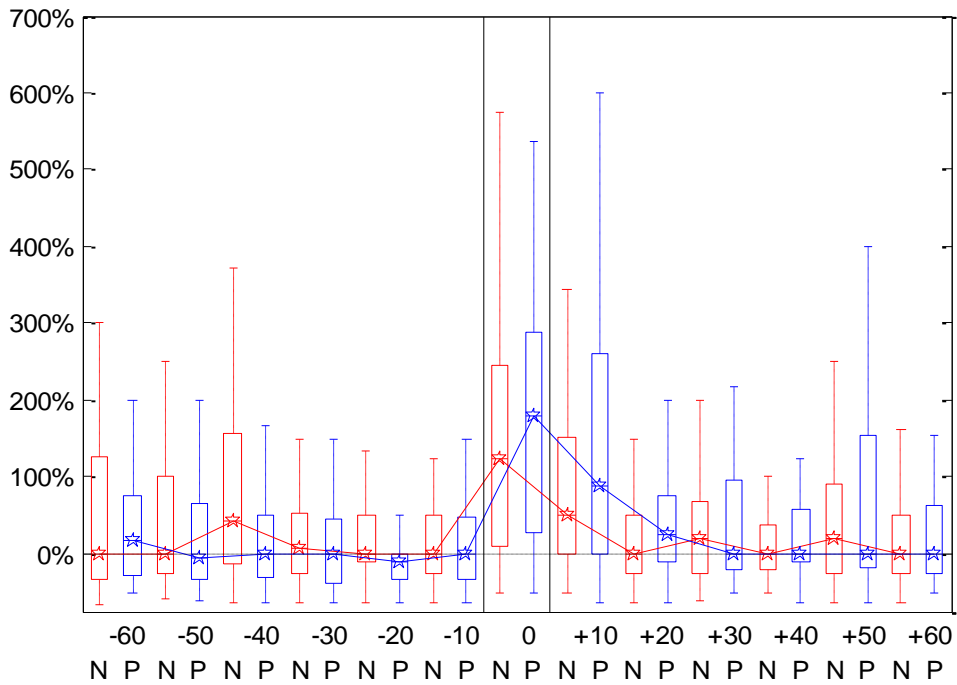


Figure 6: Volume traded (VOL) for neg. (N)/ pos. (P) jumps during the event window.

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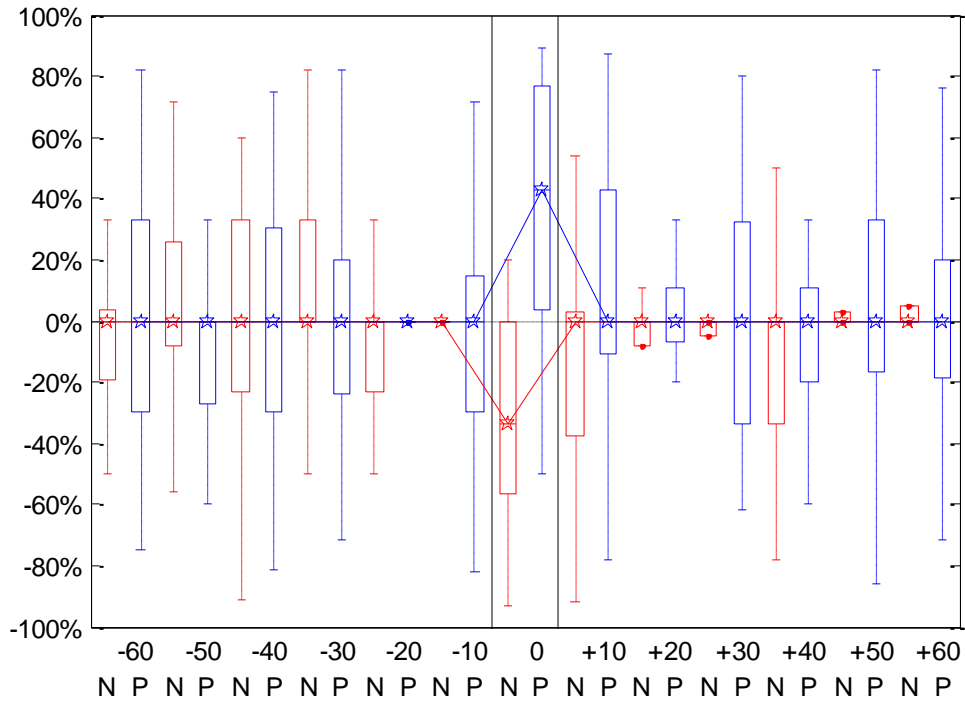


Figure 7: Order imbalance (OI) for neg. (N)/ pos. (P) jumps during the event window.

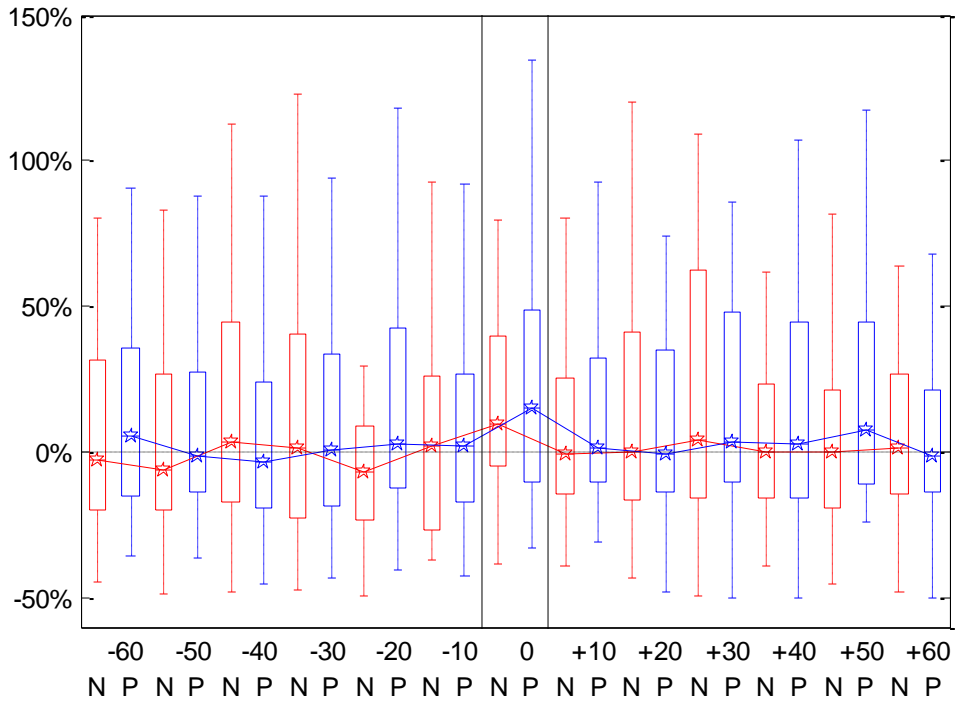


Figure 8: Mean bid depth at best quote (BRDTH_B) for neg. (N)/ pos. (P) jumps during the event window.

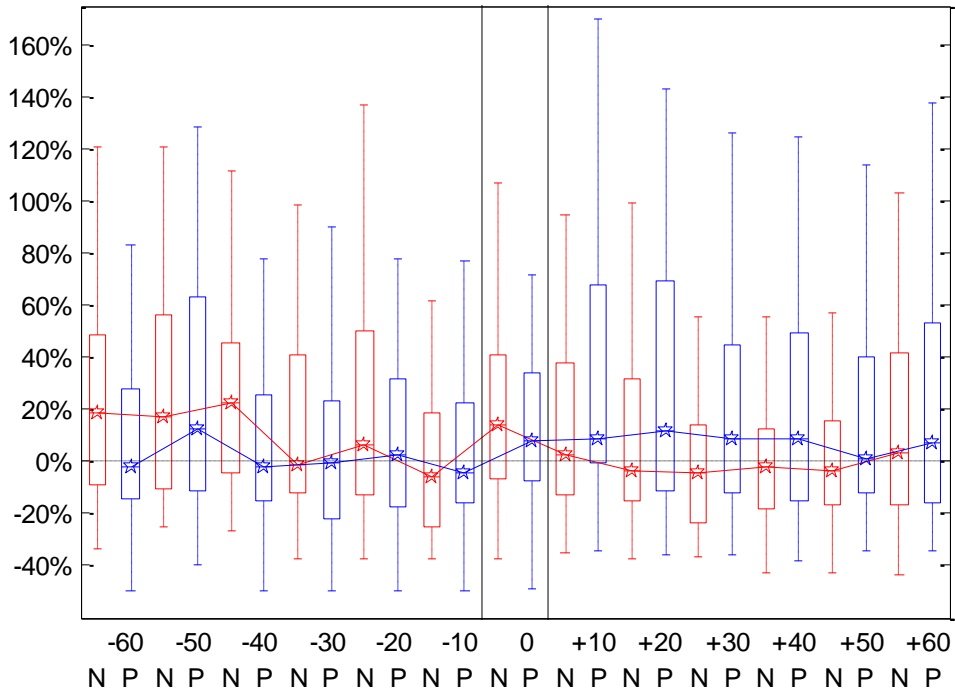


Figure 9: Mean ask depth at best quote (BRDTH_A) for neg. (N)/ pos. (P) jumps during the event window.

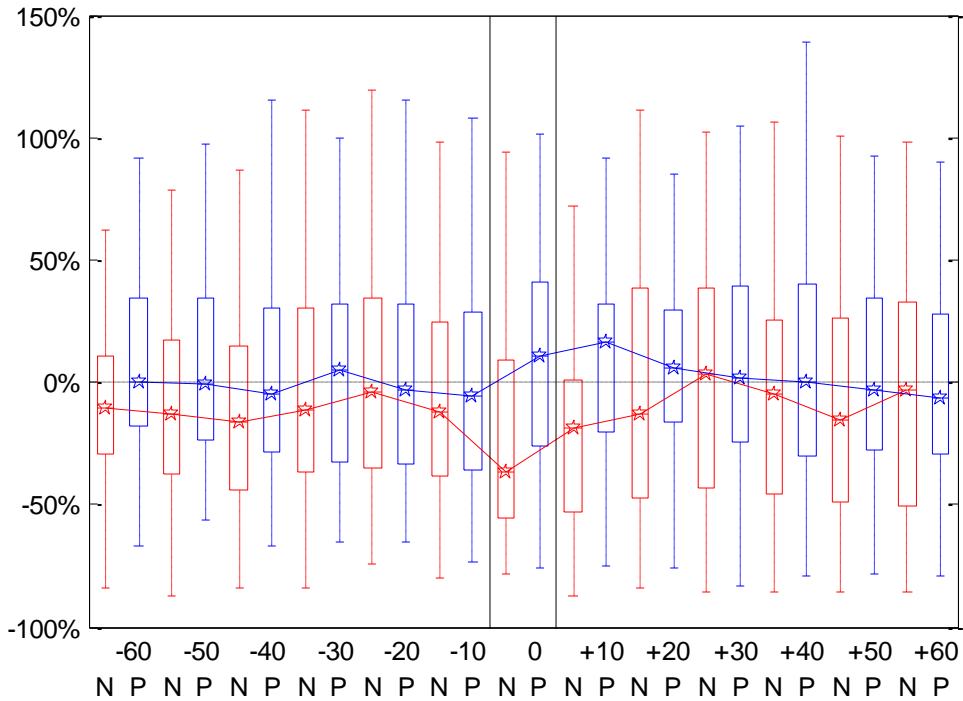


Figure 10: Mean bid depth (DPTH_B) for neg. (N)/ pos. (P) jumps during the event window.

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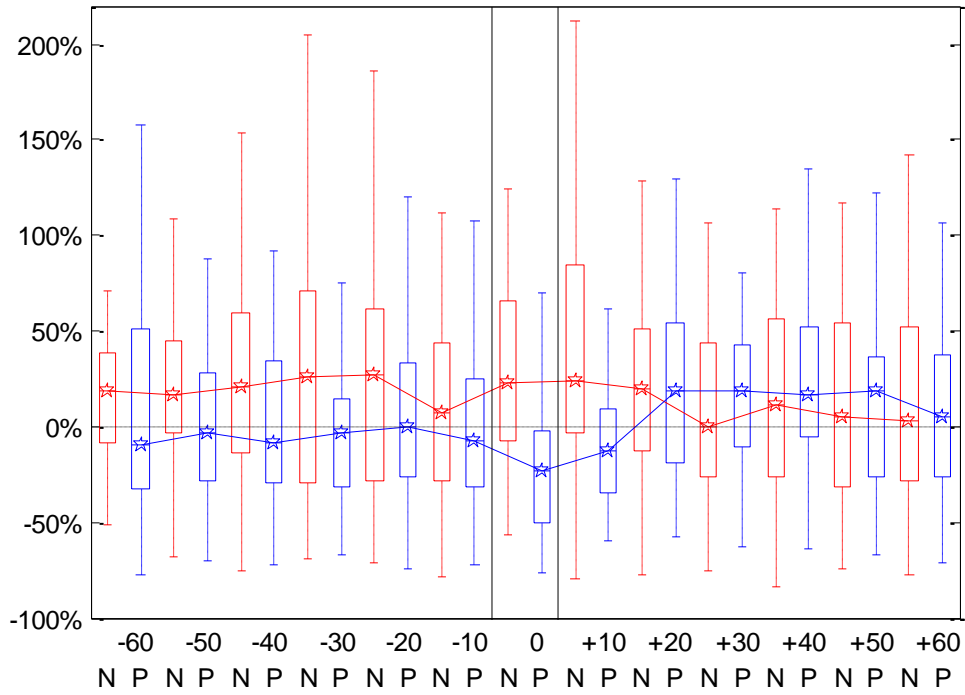


Figure 11: Mean ask depth ($DPTH_A$) for neg. (N)/ pos. (P) jumps during the event window.

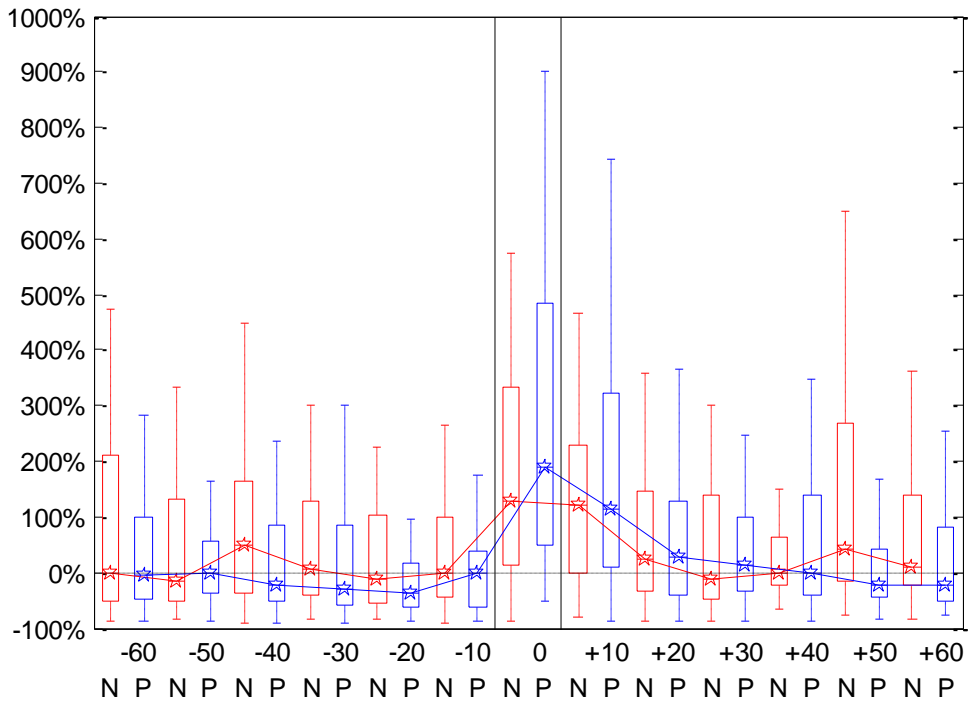


Figure 12: Volume of lim. buy orders (LOB) for neg. (N)/ pos. (P) jumps during the event window.

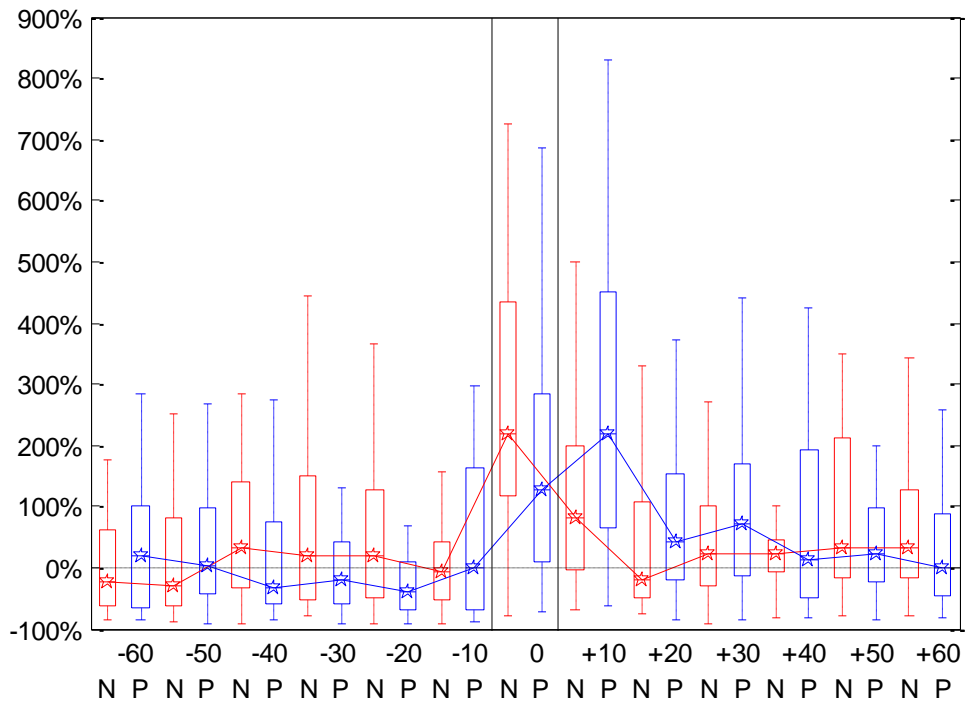


Figure 13: Volume of lim. sell orders (LO_S) for neg. (N)/ pos. (P) jumps during the event window

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TABLES

	Whole sample	2003	2004
Number of quotes	437,420	193,447	243,973
Number of trades	72,622	31,978	40,644
Average trade size	1,304,398 EUR	1,339,827 EUR	1,276,523 EUR
Trades \leq 1 million €	80.38%	78.89%	81.55%
Trades $>$ 1 million € and $<$ 3 million €	13.79%	14.50%	13.23%
Trades \geq 3 million €	5.83%	6.61%	5.22%
Average number of quotes per day	881.90	806.03	953.02
Average number of trades per day	146.42	133.24	158.77
Average daily trading volume (million €)	190.98	178.52	202.67

Table 1: Summary statistics

	2003 Jan-Jun	2003 Jul-Dec	2004 Jan-Jun	2004 Jul-Dec
Number of orders	89339	94151	114891	115416
Market orders (%)				
Bid side	8.12%	7.96%	7.52%	7.96%
Ask side	7.58%	7.58%	7.55%	7.97%
Limit orders (not exec., %)				
Bid side	29.92%	30.16%	31.23%	28.37%
Ask side	27.09%	27.95%	28.21%	26.11%
Limit orders (at least partly exec., %)				
Bid side	13.27%	12.96%	12.81%	14.71%
Ask side	14.01%	13.40%	12.67%	14.88%
Size				
Small size (1 Mill., %)	71.16%	76.03%	78.25%	75.99%
Medium size (2 Mill., %)	16.52%	14.38%	13.46%	14.24%
Large (+2 Mill., %)	12.32%	9.59%	8.29%	9.77%

Table 2: Order descriptives.

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	2003 Jan-Jun	2003 Jul-Dec	2004 Jan-Jun	2004 Jul-Dec
Average spread (HUF/EUR)	0.31	0.39	0.35	0.24
Average breadth				
Bid side	1.97	1.73	1.66	2.06
Ask side	1.84	1.67	1.54	1.63
Average depth				
Bid side	12.89	28.36	11.96	43.52
Ask side	11.38	9.67	9.70	12.66
Average number of levels				
Bid side	6.22	6.12	6.02	6.99
Ask side	5.64	5.27	5.83	7.35

Table 3: Book descriptives.

Panel A: Descriptives of the price process

	Realized Volatility	All Continuous Components	All Jump Components	Significant Jump Components
Observations	494	494	494	90
Mean (*10 ⁻³)	0.33	0.30	0.03	0.17
Median (*10 ⁻³)	0.12	0.11	0.00	0.06
Standard Deviation (*10 ⁻³)	1.40	1.39	0.16	0.35
Minimum (*10 ⁻³)	0.01	0.01	0.00	0.01
Maximum (*10 ⁻³)	28.30	28.30	2.07	2.07
Skewness	17.02	17.37	8.61	3.57
Kurtosis	329.76	339.07	87.36	16.27

Panel B: Jump characteristics

	Mean	Min.	Med.	Max.	Standard Deviation
Jump duration (in days)	6.6	1.0	6.0	28.0	5.5
Contribution to volatility (on jump day)	42.59%	11.52%	38.67%	94.08%	22.27%

Table 4: Prevalence and size of jumps.

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	Positive Jumps		Negative Jumps	
Observations	65		60	
Number of Jump Days	56		52	
	Size	Variance	Size	Variance
Mean (*10 ⁻³)	3.08	0.016	-2.54	0.010
Median (*10 ⁻³)	2.23	0.005	-1.97	0.004
Standard Deviation (*10 ⁻³)	2.50	0.030	0.184	0.016
Minimum (*10 ⁻³)	0.59	0	-8.95	0
Maximum (*10 ⁻³)	14.42	0.208	-0.61	0.080
Skewness	2.08	4.59	-1.73	3.04
Kurtosis	5.90	26.39	3.15	9.78

Table 5: Positive vs. negative jumps.

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	Time of Announcement	Number of Observations	Number of obs. that match jumps	P(Jump News)	P(News Jump)
All categories			20	< 1%	16.00%
News on Hungary					
GDP	9 am	8	2	25.00%	1.60%
Public Sector Balance	10 am/ 5 pm	24	1	4.17%	0.80%
Current Account Balance	8:30 am	24	1	4.17%	0.80%
Retail Sales	9:00 am	24	1	4.17%	0.80%
News on Germany					
CPI	8 am	24	1	4.17%	0.80%
Wholesale Price	8 am	24	1	4.17%	0.80%
Import Price	8 am	24	1	4.17%	0.80%
News on the United States					
PPI	2:30 pm	24	2	8.33%	1.60%
CPI	2:30 pm	24	1	4.17%	0.80%
Real GDP	2:30 pm	8	1	12.50%	0.80%
Tradebalance	2:30 pm	24	1	4.17%	0.80%
Consumer Confidence	4 pm	24	1	4.17%	0.80%
New Home Sales	4 pm	24	1	4.17%	0.80%
Construction Spending	4 pm	24	1	4.17%	0.80%
ISM Index	4 pm	24	1	4.17%	0.80%
News on CEEC's: Poland					
PPI	4 pm	24	2	8.33%	1.60%
Industrial Output	4 pm	24	1	4.17%	0.80%

Table 6: Jumps and scheduled macroeconomic announcements.

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	Explained by News	Explained by Scheduled Announcements	Explained by Unscheduled, Real-Time News
All jumps	58 (46.40%)	20 (16.00%)	38 (30.40%)
Ranked by size of the Jump			
Top 15	8 (53.30%)	4 (26.70%)	4 (26.70%)
Top 16 to 30	7 (46.70%)	2 (13.33%)	5 (33.33%)
Top 31 to 50	11 (55.00%)	4 (20.00%)	7 (35.00%)
Rest of the Jumps	32 (42.70%)	10 (13.33%)	22 (29.33%)

Table 7: Share of jumps explained by news announcements.

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	-60	-50	-40	-30	-20	-10	0	10	20	30	40	50	60
Tightness													
SWPQS	-5,25%	-4,36%	1,31%	0,60%	-4,72%	-1,56%	25,09%	18,03%	-3,00%	-3,06%	6,95%	6,14%	8,76%
Immediacy													
VOL	16,67%	-4,35%	0,00%	0,00%	-11,27%	0,00%	180,00%	87,50%	25,00%	0,00%	0,00%	0,00%	0,00%
OI	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	57,89%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
Depth													
DPTH _B	0,12%	-0,63%	-4,47%	5,11%	-3,54%	-5,46%	10,76%	16,50%	5,75%	1,41%	0,11%	-3,11%	-6,27%
DPTH _A	-9,55%	-3,77%	-8,74%	-3,72%	0,14%	-6,94%	-23,04%	-12,91%	19,01%	18,85%	16,99%	19,15%	4,74%
DI	-3,52%	-2,62%	0,94%	-4,16%	0,30%	0,14%	-15,81%	-8,52%	0,44%	6,93%	9,15%	6,73%	3,15%
Breadth													
BRDTH _B	5,59%	-1,63%	-3,45%	0,62%	2,74%	2,33%	14,82%	1,28%	-0,36%	3,18%	2,71%	7,67%	-1,49%
BRDTH _A	-2,39%	12,23%	-1,70%	-0,82%	2,22%	-4,57%	8,07%	8,76%	11,82%	8,76%	8,79%	0,93%	7,07%
BI	0,00%	7,00%	1,22%	0,00%	-4,23%	-0,98%	-4,50%	5,76%	3,01%	0,00%	0,00%	-3,28%	0,00%

Table 8: Liquidity dynamics around positive jumps (Light gray: significant at 10% level, medium gray: significant at 5% level, dark gray: significant at 1% level).*

* SWPQS: Size-weighted proportional quoted spread, VOL: Volume traded, OI: Order flow imbalance, DPTH_B: Mean depth at the bid side, DPTH_A: Mean depth at the ask side, DI: Mean depth imbalance, BRDTH_B: Mean depth at the best bid, BRDTH_A: Mean depth at the best ask, BI: Mean imbalance of depth at the best quotes.

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	-60	-50	-40	-30	-20	-10	0	10	20	30	40	50	60
Tightness													
SWPQS	1,69%	3,89%	2,79%	7,74%	-0,83%	-0,90%	23,88%	6,02%	2,24%	8,71%	6,77%	-3,75%	7,94%
Immediacy													
VOL	0,00%	0,00%	42,86%	6,67%	0,00%	0,00%	125,00%	50,00%	0,00%	18,92%	0,00%	20,00%	0,00%
OI	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	-33,33%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
Depth													
DPTH _B	-10,65%	-12,63%	-16,24%	-11,08%	-4,30%	-11,83%	-37,07%	-18,77%	-12,69%	3,33%	-4,98%	-15,35%	-2,97%
DPTH _A	18,30%	16,36%	20,77%	25,60%	27,18%	7,56%	22,46%	24,11%	19,30%	-0,07%	11,40%	4,91%	2,49%
DI	10,56%	8,93%	14,83%	16,30%	10,15%	5,27%	20,08%	19,02%	14,84%	9,69%	4,93%	10,07%	2,31%
Breadth													
BRDTH _B	-2,70%	-5,92%	3,76%	1,25%	-6,65%	2,14%	9,59%	-0,63%	0,00%	4,26%	-0,02%	0,00%	1,46%
BRDTH _A	18,48%	17,19%	22,57%	-1,57%	6,60%	-5,71%	13,98%	2,54%	-3,53%	-4,64%	-1,88%	-3,46%	3,69%
BI	2,03%	7,69%	0,00%	1,21%	9,58%	-1,59%	-1,04%	5,00%	0,00%	0,00%	0,00%	0,00%	0,00%

Table 9: Liquidity dynamics around negative jumps (Light gray: significant at 10% level, medium gray: significant at 5% level, dark gray: significant at 1% level).*

* SWPQS: Size-weighted proportional quoted spread, VOL: Volume traded, OI: Order flow imbalance, DPTH_B: Mean depth at the bid side, DPTH_A: Mean depth at the ask side, DI: Mean depth imbalance, BRDTH_B: Mean depth at the best bid, BRDTH_A: Mean depth at the best ask, BI: Mean imbalance of depth at the best quotes.

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	α	β_1	β_2	β_3	β_4	β_5	γ	Adj. R ²	Log-L	Chi-square	F-test
Panel A: Probit regression											
Coeff.	-1.953	-18.319	-0.013	-0.300	-0.067	-0.576	2.028	6.70%	-288.11	7.45	
NW s.e.	0.093	20.138	0.033	0.220	0.163	0.441	0.316				
Test stat.	-21.090	-0.910	-0.410	-1.360	-0.410	-1.310	6.420				
p-value	0.000	0.363	0.685	0.172	0.683	0.192	0.000			0.19	
Panel B: Tobit regression											
Coeff.	-0.013	-0.058	-0.0001	-0.002	-0.0006	-0.004	0.013	6.84%	17.72		2.1
NW s.e.	0.001	0.041	0.0002	0.001	0.001	0.003	0.002				
Test stat.	-9.450	-1.410	-0.470	1.320	-0.550	-1.320	5.790				
p-value	0.000	0.157	0.636	0.188	0.584	0.187	0.000				0.0627

Table 10: Probit regression of the jump probability and Tobit regression of the jump magnitude

	α_0	α_1	β_0	β_1	β_2	Adj. R ²
Specification 1						
Coeff.	-0.000	-0.006		0.008	-0.003	22.19%
NW s.e.	0.000	0.004		0.001	0.001	
Test stat.	-0.640	-1.470		9.730	-2.500	
p-value	0.525	0.142		0.000	0.012	
Specification 2						
Coeff.	-0.000	-0.006	-0.001	0.008	-0.003	22.70%
NW s.e.	0.000	0.004	0.000	0.001	0.001	
Test stat.	-0.530	-1.370	-3.650	9.790	-2.380	
p-value	0.597	0.170	0.000	0.000	0.018	

Table 11: Regression of price change on order flow.

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Resiliency after positive jumps

	0	10	20	30	40	50	60
LO _B	188,89%	112,89%	26,87%	14,64%	0,00%	-22,22%	-23,02%
LO _S	127,27%	220,00%	42,86%	70,73%	14,29%	22,61%	0,00%
LOI	13,58%	-8,33%	-0,37%	-5,26%	0,00%	0,00%	0,00%
LO _{BB}	233,33%	100,00%	0,00%	-11,11%	0,00%	0,00%	-25,00%
LO _{SB}	108,33%	185,71%	33,33%	13,95%	1,96%	1,96%	-16,67%
LOI _B	14,29%	-11,58%	0,00%	0,00%	0,00%	0,00%	0,00%

Resiliency after negative jumps

	0	10	20	30	40	50	60
LO _B	126,67%	122,22%	25,00%	-12,50%	0,00%	40,63%	11,24%
LO _S	220,00%	82,11%	-18,37%	23,60%	23,60%	33,33%	33,33%
LOI	-15,00%	6,89%	0,00%	0,00%	0,00%	0,00%	0,00%
LO _{BB}	122,22%	80,00%	0,00%	0,00%	11,11%	12,50%	23,08%
LO _{SB}	250,00%	55,56%	0,00%	0,00%	20,00%	33,33%	25,00%
LOI _B	-27,87%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%

Table 12: Resiliency after jumps (Light gray: significant at 10% level, medium gray: significant at 5% level, dark gray: significant at 1% level).*

* LO_B: Volume of limit buy orders submitted, LO_S: Volume of limit sell orders submitted, LOI: Imbalance of the volume of limit orders submitted, LO_{BB}: Volume of limit orders entered at the best buy, LO_{SB}: Volume of limit orders entered at the best sell, LOI_B: Imbalance of the limit orders entered at the best quote.

	α_0	α_1	β_0	β_1	ρ_1	Adj. R ²
Coeff.	-0.006	-0.078	-0.139	0.988	-0.271	6.21%
NW s.e.	0.051	0.066	0.121	0.412	0.024	
Test stat.	-0.110	-1.190	-1.150	2.400	-11.270	
p-value	0.910	0.234	0.252	0.017	0.000	

Table 13: Regression of depth change on lagged transitory volatility.

APPENDIX I: DEFINITION OF LIQUIDITY MEASURES

SWPQS	The size-weighted proportional quoted spread, defined as the weighted average of the quoted spread per 10 minute interval. The weighting scheme uses the quantities available at the prevailing quotes as the weight.
NT	Number of trades, defined as the total number of transaction per 10 minute interval.
VOL	Trading volume, defined as the total transaction volume by value per 10 minute interval.
OF	(Transaction) Order flow, defined as the signed trading volume per 10 minute interval.
OI	Order flow imbalance, defined as the ratio of transaction order flow to the total transaction volume by value per 10 minute interval.
DPTH _B	Mean depth at the bid side, defined as the average quantity available at the bid side of the limit order book over all quotes per 10 minute interval.
DPTH _A	Mean depth at the ask side, defined as the average quantity available at the ask side of the limit order book over all quotes per 10 minute interval.
DI	Depth imbalance, defined as the difference between DPTH _A and DPTH _B scaled by the sum of DPTH _A and DPTH _B per 10 minute interval.
BRDTH _B	Mean breadth at the bid side, defined as the average quantity available at the best bid of the limit order book over all quotes per 10 minute interval.
BRDTH _A	Mean breadth at the ask side, defined as the average quantity available at the best ask of the limit order book over all quotes per 10 minute interval.
BI	Breadth imbalance, defined as the difference between BRDTH _A and BRDTH _B scaled by the sum of BRDTH _A and BRDTH _B per 10 minute interval.
LO _B	Limit buy order submitted, defined as the quantities (volume) of newly placed limit buy orders per 10 minute interval.
LO _S	Limit sell order submitted at the best price, defined as the quantities (volume) of newly placed limit sell orders per 10 minute interval.
LOI	Limit order imbalance, defined as the difference between LO _B and LO _S , scaled by the sum of LO _B and LO _S per 10 minute interval.
LO _{BB}	Limit buy order submitted at the best price, defined as the quantities (volume) of newly placed limit buy orders at the best price per 10 minute interval.
LO _{SB}	Limit sell order submitted at the best price, defined as the quantities (volume) of newly placed limit sell orders at the best price per 10 minute interval.
LOI _B	Limit order imbalance at the best price, defined as the difference between LO _{BB} and LO _{SB} , scaled by the sum of LO _{BB} and LO _{SB} per 10 minute interval.

APPENDIX II: STANDARDIZATION OF THE LIQUIDITY MEASURES

It is well known in the empirical literature that liquidity measures have seasonal patterns at the daily and intraday level whether they are compounded with news announcements or not (eg. see figure 1 Fleming & Remolona 1999). Therefore, liquidity measures need to be standardized to make them comparable across days and intraday periods. Moreover, the empirical distribution of liquidity measures is highly skewed to the right at the intraday level as pointed out by Plerou *et al.* (2005) among others. Motivated by the applications in Boudt and Petitjean (201x); Boudt *et al.* (2011), we favor median value rather than mean value for standardizing purpose, which deviates from previous literature ((Fleming & Remolona 1999; Jiang *et al.* 2011; Gomber *et al.* 2013).

Following Boudt and Petitjean (201x), we assume that all the liquidity measures except spread and imbalance measures follow a multiplicative specification: On non-jump days, the intraday value of the liquidity measure (denoted as $LM_{i,j}$) is the product of a latent daily factor LM_i and a deterministic intradaily factor LM_j and an *i.i.d.* error term $\varepsilon_{i,j}$ with median 1.

$$LM_{i,j} = LM_i LM_j \varepsilon_{i,j} \quad [\text{AII.1}]$$

On jump days, however, the above specification is augmented by an additive component $\delta_{i,j}$ associated with jumps:

$$LM_{i,j} = LM_i LM_j \varepsilon_{i,j} + \delta_{i,j} \quad [\text{AII.2}]$$

Given the above assumptions, the sample counterpart of the daily factor (\widehat{LM}_i) is proxied by the median value of the intraday liquidity measure on day i , while the sample intraday factor (\widehat{LM}_j) is estimated as the sample median of all the observed intraday liquidity values in interval j on non-jump days (NJD), scaled by their respective daily factor.

$$\widehat{LM}_j = \text{median}_{i \in NJD} \frac{\widehat{LM}_{i,j}}{\widehat{LM}_i} \quad [\text{AII.3}]$$

It is thus straightforward to calculate the percentage deviation of the liquidity value from its normal (expected) level via the following equation.

$$\widetilde{LM}_{i,j} = \frac{\widehat{LM}_{i,j}}{\widehat{LM}_i \widehat{LM}_j} - 1 \quad [\text{AII.4}]$$

where the first term in the RHS of the equation is the standardized liquidity measure.

As the imbalance measures are bounded in (-1, +1), we opt for an additive process with the following specification:

$$LM_{i,j} = LM_i + LM_j + \varepsilon_{i,j} + \delta_{i,j} \quad [\text{AII.5}]$$

with $\varepsilon_{i,j}$ as an *i.i.d.* error term with zero median and $\delta_{i,j}$ as an additive component due to jumps. In the same token, the estimated daily factor (\widehat{LM}_i) is proxied by the median value of the intraday liquidity measure on day i . The sample intraday factor (\widehat{LM}_j), however, is estimated as the sample median of all the observed intraday liquidity values in interval j on non-jump days (NJD), net of their respective daily factor:

$$\widehat{LM}_j = \text{median}_{i \in NJD} (\widehat{LM}_{i,j} - \widehat{LM}_i) \quad [\text{AII.6}]$$

The deviation of the liquidity value is thus:

$$\widetilde{LM}_{i,j} = \widehat{LM}_{i,j} - \widehat{LM}_i - \widehat{LM}_j \quad [\text{AII.7}]$$

Therefore, we use the above equation to estimate the deviation for liquidity measures including depth imbalance, order imbalance, imbalance of newly placed limit orders and spread.

Chapter 2

For either of the model specification, we would expect the median value of $\widetilde{LM}_{i,j}$ to be zero in case of no (significant) jump effect on liquidity.

LIST OF REFERENCES

- Acharya, V.V., Pedersen, L.H., 2005. Asset pricing with liquidity risk. *Journal of Financial Economics* 77, 375-410
- Admati, A., Pfleiderer, P., 1988. A theory of intraday patterns: volume and price variability. *Review of Financial Studies* 1, 3-40
- Ahn, H.-J., Bae, K.-H., Chan, K., 2001. Limit Orders, Depth, and Volatility: Evidence from the Stock Exchange of Hong Kong. *The Journal of Finance* 56, 767-788
- Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets* 5, 31-56
- Anand, A., Venkataraman, K., 2013. Should Exchanges Impose Market Maker Obligations? Available at SSRN: <http://ssrn.com/abstract=2179259> or <http://dx.doi.org/10.2139/ssrn.2179259>
- Andersen, T.G., Bollerslev, T., Diebold, F.X., 2007a. Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *Review of Economics and Statistics* 89, 701-720
- Andersen, T.G., Bollerslev, T., Dobrev, D., 2007b. No-arbitrage semi-martingale restrictions for continuous-time volatility models subject to leverage effects, jumps and iid noise: Theory and testable distributional implications. *Journal of Econometrics* 138, 125
- Andersen, T.G., Bollerslev, T., Frederiksen, P., Ørregaard Nielsen, M., 2010. Continuous-time models, realized volatilities, and testable distributional implications for daily stock returns. *Journal of Applied Econometrics* 25, 233-261
- Bajgrowicz, P., Scaillet, O., 2011. Jumps in High-Frequency Data: Spurious Detections, Dynamics, and News. SSRN eLibrary
- Banti, C., Phylaktis, K., Sarno, L., 2012. Global liquidity risk in the foreign exchange market. *Journal of International Money and Finance* 31, 267-291
- Barndorff-Nielsen, O.E., Shephard, N., 2004. Power and Bipower Variation with Stochastic Volatility and Jumps. *Journal of Financial Econometrics* 2, 1-37
- Barndorff-Nielsen, O.E., Shephard, N., 2006a. Econometrics of Testing for Jumps in Financial Economics Using Bipower Variation. *Journal of Financial Econometrics* 4, 1-30
- Barndorff-Nielsen, O.E., Shephard, N., 2006b. Impact of jumps on returns and realised variances: econometric analysis of time-deformed Levy processes. *Journal of Econometrics* 131, 217-252
- Beine, M., Lahaye, J., Laurent, S., Neely, C.J., Palm, F.C., 2007. Central bank intervention and exchange rate volatility, its continuous and jump components. *International Journal of Finance & Economics* 12, 201
- Biais, B., Hillion, P., Spatt, C., 1995. An Empirical Analysis of the Limit Order Book and the Order Flow in the Paris Bourse. *The Journal of Finance* 50, 1655-1689
- BIS, 1996. Triennial central bank survey: report on global foreign exchange market activity in 1996. Bank for International Settlements, www.bis.org
- BIS, 2005. Triennial central bank survey: report on global foreign exchange market activity in 2005. Bank for International Settlements, www.bis.org
- BIS, 2010. Triennial central bank survey: report on global foreign exchange market activity in 2010. Bank for International Settlements, www.bis.org
- Bloomfield, R., O'Hara, M., Saar, G., 2005. The “make or take” decision in an electronic market: Evidence on the evolution of liquidity. *Journal of Financial Economics* 75, 165-199
- Boudt, K., Croux, C., Laurent, S., 2011. Robust estimation of intraweek periodicity in volatility and jump detection. *Journal of Empirical Finance* 18, 353-367

- Boudt, K., Petitjean, M., 201x. Intraday liquidity dynamics and news releases around price jumps: Evidence from the DJIA stocks. *Journal of Financial Markets*, forthcoming
- Campbell, J.Y., Grossman, S.J., Wang, J., 1993. Trading Volume and Serial Correlation in Stock Returns. *The Quarterly Journal of Economics* 108, 905-939
- Cao, C., Hansch, O., Wang, X., 2008. Order Placement Strategies in a Pure Limit Order Book Market. *Journal of Financial Research* 31, 113-140
- Cohen, K.J., Maier, S.F., Schwartz, R.A., Whitcomb, D.K., 1981. Transaction Costs, Order Placement Strategy, and Existence of the Bid-Ask Spread. *Journal of political economy* 89, 287-305
- Copeland, L.S., 2005. *Exchange Rates and International Finance*. Prentice Hall, Harlow.
- Covrig, V., Ng, L., 2004. Volume autocorrelation, information, and investor trading. *Journal of Banking & Finance* 28, 2155-2174
- Dungey, M., McKenzie, M., Smith, L.V., 2009. Empirical evidence on jumps in the term structure of the US Treasury Market. *Journal of Empirical Finance* 16, 430-445
- Eisler, Z., Bouchaud, J.-P., Kockelkoren, J., 2011. The price impact of order book events: market orders, limit orders and cancellations. *Quantitative Finance* 12, 1395-1419
- Evans, K.P., 2011. Intraday jumps and US macroeconomic news announcements. *Journal of Banking & Finance* 35, 2511-2527
- Evans, M.D.D., Lyons, R.K., 2002. Informational integration and FX trading. *Journal of International Money and Finance* 21, 807-831
- Evans, M.D.D., Lyons, R.K., 2005. Meese-Rogoff Redux: Micro-Based Exchange-Rate Forecasting. *The American economic review* 95, 405-414
- Fleming, M.J., Remolona, E.M., 1999. Price Formation and Liquidity in the U.S. Treasury Market: The Response to Public Information. *The Journal of Finance* 54, 1901-1915
- Foucault, T., 1999. Order flow composition and trading costs in a dynamic limit order market. *Journal of Financial Markets* 2, 99-134
- Foucault, T., Kadan, O., Kandel, E., 2005. Limit Order Book as a Market for Liquidity. *Review of Financial Studies* 18, 1171-1217
- Foucault, T., Kadan, O., Kandel, E., 2013. Liquidity Cycles and Make/Take Fees in Electronic Markets. *The Journal of Finance* 68, 299-341
- Frömmel, M., Kiss M, N., Pintér, K., 2011. Macroeconomic announcements, communication and order flow on the Hungarian foreign exchange market. *International Journal of Finance & Economics* 16, 172-188
- Frömmel, M., Van Gysegem, F., 2012. Spread Components in the Hungarian Forint-Euro Market. *Emerging Markets Finance & Trade* 48, 52-69
- Gereben, Á., Kiss M., N., 2006. A Brief Overview of the Characteristics of Interbank Forint/Euro Trading. *MNB Bulletin* 1:2
- Glosten, L.R., 1994. Is the Electronic Open Limit Order Book Inevitable? *The Journal of Finance* 49, 1127-1161
- Goettler, R.L., Parlour, C.A., Rajan, U., 2005. Equilibrium in a Dynamic Limit Order Market. *The Journal of Finance* 60, 2149-2192
- Gomber, P., Schweickert, U., Theissen, E., 2013. Liquidity Dynamics in an Electronic Open Limit Order Book: an Event Study Approach. *European Financial Management*, n/a-n/a
- Griffiths, M.D., Smith, B.F., Turnbull, D.A.S., White, R.W., 2000. The costs and determinants of order aggressiveness. *Journal of Financial Economics* 56, 65-88
- Harris, L., 1998. Optimal Dynamic Order Submission Strategies in Some Stylized Trading Problems. *Financial Markets, Institutions & Instruments* 7, 1-76
- Hautsch, N., Huang, R., 2012. The market impact of a limit order. *Journal of Economic Dynamics and Control* 36, 501-522

- Hollifield, B., Miller, R.A., Sandås, P., 2004. Empirical Analysis of Limit Order Markets. *The Review of Economic Studies* 71, 1027-1063
- Huang, X., 2007. Macroeconomic News Announcements, Financial Market Volatility and Jumps.
- Huang, X., Tauchen, G., 2005. The Relative Contribution of Jumps to Total Price Variance. *Journal of Financial Econometrics* 3, 456-499
- Jiang, G.J., Lo, I., Verdelhan, A., 2011. Information Shocks, Liquidity Shocks, Jumps, and Price Discovery: Evidence from the US Treasury Market. *Journal of Financial and Quantitative Analysis* 46, 527-551
- Jiang, G.J., Oomen, R.C.A., 2008. Testing for jumps when asset prices are observed with noise—a “swap variance” approach. *Journal of Econometrics* 144, 352-370
- Kaniel, R., Liu, H., 2006. So What Orders Do Informed Traders Use? *The Journal of Business* 79, 1867-1913
- Kozhan, R., Moore, M.J., Payne, R., 2012. Market order flows, limit order flows and exchange rate dynamics.
- Kyle, A.S., 1985. Continuous Auctions and Insider Trading. *Econometrica* 53, 1315-1335
- Lahaye, J., Laurent, S., Neely, C.J., 2011. Jumps, Cojumps and Macro Announcements. *Journal of Applied Econometrics* 26, 893-921
- Lee, S.S., Mykland, P.A., 2008. Jumps in Financial Markets: A New Nonparametric Test and Jump Dynamics. *Review of Financial Studies* 21, 2535-2563
- Liu, W., 2006. A liquidity-augmented capital asset pricing model. *Journal of Financial Economics* 82, 631-671
- Mazza, P., 2013. Rethinking Zero Returns in the Liquidity Puzzle. In: Working Paper
- Neely, C.J., 2011. A Survey of Announcement Effects on Foreign Exchange Volatility and Jumps. *Federal Reserve Bank of St. Louis Review* 93, 361-385
- Parlour, C., 1998. Price dynamics in limit order markets. *Review of Financial Studies* 11, 789-816
- Pástor, L., Stambaugh, Robert F., 2003. Liquidity Risk and Expected Stock Returns. *Journal of political economy* 111, 642-685
- Plerou, V., Gopikrishnan, P., Stanley, H.E., 2005. Quantifying fluctuations in market liquidity: Analysis of the bid-ask spread. *Physical Review E* 71, 046131
- Ranaldo, A., 2004. Order aggressiveness in limit order book markets. *Journal of Financial Markets* 7, 53-74
- Rime, D., 2000. Private or Public Information in Foreign Exchange Markets? An Empirical Analysis. SSRN eLibrary
- Roşu, I., 2009. A Dynamic Model of the Limit Order Book. *Review of Financial Studies* 22, 4601-4641
- Sager, M.J., Taylor, M.P., 2006. Under the microscope: the structure of the foreign exchange market. *International Journal of Finance & Economics* 11, 81-95
- Sandås, P., 2001. Adverse Selection and Competitive Market Making: Empirical Evidence from a Limit Order Market. *Review of Financial Studies* 14, 705-734
- Seppi, D., 1997. Liquidity provision with limit orders and a strategic specialist. *Review of Financial Studies* 10, 103-150
- Wang, J., 1994. A Model of Competitive Stock Trading Volume. *Journal of political economy* 102, 127-168

Chapter 3

**Spread Components in the
Hungarian Forint-Euro Market:
Evidence from a Theoretical Spread
Decomposition Model**

Spread Components in the Hungarian Forint- Euro Market: Evidence from a Theoretical Spread Decomposition Model*

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Abstract

We apply the spread decomposition model by Huang and Stoll (1997) to a new dataset on the Hungarian forint/ euro interbank market. In contrast to previous results we cover a minor market over a long time span. We find a significant inventory effect and we find that spread size significantly increases with trade size. Overall this work confirms the predictions from various theoretical models on a small and less liquid market. In comparison with other studies the size of the market, institutional differences between markets and specificities of a dataset seem to play an important role.

JEL: F31, G15

Keywords: microstructure, foreign exchange, spread, Hungary, inventory, adverse selection

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Spread Components in the Hungarian Forint- Euro Market: Evidence from a theoretical spread decomposition model

1. Introduction

Since a well-functioning foreign exchange market is of crucial importance for the economy, which is particularly true in the case of small open economies as most of the Central and Eastern European Countries (CEEC's), there is a deep interest in the way it works. The microstructure approach to foreign exchange (see Lyons 2001) allows for market frictions, such as imperfect information and heterogeneous agents, and tries to explain the processing of news (price discovery), liquidity and the transaction costs on a market. In this context the bid-ask spread and its determinants play a crucial role. The decomposition of the bid-ask spread on financial markets has attracted increasing attention during the last decades for several reasons. It is important as an indicator of market liquidity and competition, but also reflects the way information is processed in the market. This is important because a different market structure changes the "game played between the market participants" (Rime 2003, p. 471). It is therefore relevant for market participants, but also for the operators of markets in terms of an evaluation of the market design. The microstructure approach to foreign exchange markets has made some promising steps towards a better understanding of the foreign exchange market.

The bid-ask spread is the difference between the price an active buyer must pay, and the revenue an active seller receives.¹ It is common to relate the size of the spread to various kinds of cost components: the *order processing* (or handling) *component*, the *adverse selection component* and the *inventory holding component*.² We contribute to the literature by exploiting a new dataset on the Hungarian foreign exchange market. Since this is the first detailed dataset available for a transition economy, it enables us to compare the spread components on a small and less liquid market to those of previous studies that mainly focused on major currencies. One may expect that components directly related to the liquidity of the market, namely the order processing and the inventory holding component, will be more

¹ One counterpart of a trade can be viewed as an active party and one counterpart as a passive party. The party that posts quotes and waits until they will be hit by another market participant is the passive party. The party that matches an existing limit order by a market or another limit order is the active party.

² One may also distinguish components for the option effect and non competitive pricing (see for example Stoll 2003). This is, however, less common. Therefore we do not follow these directions. We see the option effect as part of the adverse selection component.

important in transition economies than in the foreign exchange market for major currencies. There may also be more private information on a market on which trading is less intensive. We investigate whether this is reflected in a higher adverse selection component. Furthermore, the sample size of our dataset exceeds the size of most other datasets used in the literature by far. Finally, we will re-examine the relation between trade size and spread, which has been controversially discussed in the literature.

2. The foreign exchange market and data description

The foreign exchange market is a two-tier market. Trades on the foreign exchange market can be divided into customer trades, i.e. trades between a bank and customers (the ultimate end-users, for instance importing and exporting firms, mutual or hedge funds, governments and central banks) and interbank trades. In the following we focus on the interbank market, as the price formation takes place here. Customers do not have access to this interbank market. The majority of trades on this market are nowadays done via electronic broking systems. Since their introduction in 1992 their share in total transaction volume has steadily increased, depending on the country, from 4 to 6 per cent in 1995 to more than 55% of the interbank market in 2010 (BIS 1996, BIS 2010).

There are two main platforms competing in the foreign exchange market: Reuters D3000 and EBS (Electronic Broking System). In our analysis we rely on the Reuters D3000 system. As an electronic limit order book it contains buy and sell orders in a price-time priority. Euro sale and purchase offers are placed at limit prices. Besides these limit orders, consisting of the maximum respectively minimum price and the quantity offered to be traded, it is also possible to place a market order, i.e., an order without a specified price. They are immediately matched with the best corresponding limit order and thus more aggressive. Therefore the following matches may lead to a trade: two limit orders that are matched up by the system, or a market order that is matched up with the best limit order on the opposite side.

Our dataset consists of all quotes, i.e., limit and market orders, on the HUF/EUR interbank market that have been placed during the years 2003 and 2004 via the Reuters D3000 broking system. We observe the price, the quantity in Euro that was offered or asked, whether it was a market or a limit order and the exact time when the order was placed and when it disappeared. We observe whether the order was withdrawn or whether it was executed, i.e., matched with another limit or market order. Using this information we can identify the executed trades that we need for the estimation of the empirical model by HS1997. Because at this time the

competing system EBS did not offer services for the HUF/EUR market, the dataset covers the complete trading on electronic brokerage platforms, and thus the major part of market activity on this minor market (trade in HUF accounted during our sample period in 2004 for only 0.22% of the global turnover on the FX market (BIS 2005). For descriptive statistics of the dataset see Table 1. An in-depth description of the dataset can be found in Gereben and Kiss M. (2006).

3. The analysis of spreads

This section describes the different components of the spread. For a detailed discussion of these components see Stoll (2003).

The *order processing component (OPC)* is the cost component that is most closely linked to the provision of services. The OPC includes the costs of labour and capital needed to participate in the market, such as the floor space rent, computer and informational service, and labour costs.

The *inventory holding component (IHC)* compensates dealers for taking an unwanted inventory. If a dealer located in the Euro area for example buys Hungarian forint, he has to carry inventory costs. These costs mainly stem from two sources: first, there may be opportunity costs of tying up funds in the inventory. However, one may assume that the opportunity costs of the inventory are low on foreign exchange markets in comparison to equity markets. Second, a dealer experiences a substantial amount of risk: the price may change due to the arrival of news before he is able to offset his undesired inventory in forint. Thus, the inventory holding component represents this fundamental risk. The magnitude of the inventory costs depends on price volatility³, since higher volatility means a higher risk of an undesired price change, and on the expected time the inventory has to be held. Both are, at least to some extent, determined by the trading frequency. Therefore the inventory holding component is obviously expected to be higher on small, less liquid markets as the HUF/EUR market where on average only every three minutes one deal is executed, whereas the time between subsequent trades on major markets does not span more than a few seconds. On a limit order market, volatility is closely linked to the depth of the order book: the more limit orders in the book, the lower the volatility (Ahn et al. 2001, Chen & Wu 2009).

³ There is a triangular relation between volatility, news and the inventory risk. While the fundamental risk is per definition related to the arrival of news, empirical research also finds evidence for a close relation between news arrival and volatility, see e.g. Frömmel et al. 2008, Lin et al., 2010. A news-volatility relation is also confirmed for the Hungarian foreign exchange market (Frömmel et al. 2011).

Finally, market participants face the risk of trading with a counterpart that is better informed. If an investor has superior information, he will sell forint if he has information justifying a lower price than the current one, or vice versa. The market participants may take this possibility into account when offering their quotes and ask an additional compensation, to which we will refer as the *adverse selection component (ASC)* of the spread. The existence of an ASC is justified by a couple of theoretical papers, such as Kyle (1985), Easley and O'Hara (1987) or Admati and Pfleiderer (1988). Besides these theoretical papers, empirical research provides evidence for the existence of an ASC (see Table 4).

Previous research on foreign exchange market spreads focused on larger, more liquid markets. In a seminal paper Lyons (1995) applies microstructure models to the USD/DEM market and finds evidence for both an inventory and an asymmetric information effect, and again evidence for inventory control in Lyons (1998). The existence of both effects in the data is supported by Yao (1998). In contrast, Mende (2005) only finds a significant adverse selection component, but no consistent inventory effect. Using a VAR approach, Payne (2005) finds that about 60 per cent of the spread is due to asymmetric information. All these studies focus on the most liquid Deutsche mark (euro)/US dollar market. McGroarty et al. (2007) compare the results achieved by the HS1997 model for different major currencies (euro, US dollar, Japanese yen and Swiss franc).

In contrast few studies have been performed on spreads on smaller foreign exchange markets. An exception is Bjønnes and Rime (2005), who investigate the behaviour of a Norwegian Krona/Deutsche Mark dealer. They again find a significant asymmetric information component, but no inventory effect. For emerging markets in general and the Central- and Eastern European countries in specific there is to our knowledge no similar work.⁴

Another strand of literature deals with the relationship between order size and the bid-ask spread. There are essentially three theoretical directions which can be followed to link order size and spread: processing cost models, inventory risk models and information cost models. While the first direction suggests that increasing trade size does not increase spreads (see Stoll 1978, Hartmann 1999), inventory risk models and information cost models conclude that there should be a positive relation between trade size and spreads (see for instance Ho and Stoll 1981 for inventory costs, Kyle 1985, Admati and Pfleiderer 1988 for adverse selection costs). Similarly, the empirical research on the relation between trade size and spread has

⁴ Intuitively we would expect higher spreads on these markets. For equity markets Chae & Wang (2009) find higher spreads for less liquid market segments. In this sense we would expect to find higher spreads for smaller currencies when compared to bigger currencies.

provided mixed results. While Lyons (1995) finds a positive relation between order size and spreads, most studies conclude that there is little or no relationship between spread and order size (Yao 1998, Bjønnes and Rime 2005). The distinction between the customer and the interbank market is here also important: on the customer market strategic considerations are more important when setting spreads (Naik et al. 1999). This difference between the customer and interbank market is also empirically supported: on the customer market a negative relation between trade size and spread size is found in the trading behaviour of a small bank in Germany on the USD/EUR market (Osler et al. 2010). For an online FX dealer on the interdealer USD/EUR market the spread is found to be independent from order size (Ding 2009). Mende (2005) distinguishes between commercial customers (mainly nonfinancial corporations), financial customers (such as investment funds), and interbank trades. He finds that the asymmetric information component of spreads increases with order size only for more informed counterparties, i.e., financial customers and other banks, although the spreads for these trade partners are smaller than those for commercial customers. For an emerging market the relation between trade size and information content, which is one of the elements that determine the spread size, is found to be positive (Kang and Ryu 2010).⁵

4. Empirical model

There have been various attempts to estimate the different spread components, which can be broadly categorized into covariance based models (Stoll 1989, George et al. 1991) and models based on trade indicators (e.g. Madhavan et Smidt 1991, HS 1997). The models by Madhavan and Smidt (1991) and HS1997 have become the workhorse of spread decomposition. We apply the well established HS1997 model, which has the advantage of being widely used and at the same time to provide estimates for the adverse selection and the inventory holding component separately in its most advanced form (in contrast to the Madhavan and Smidt 1991 model). The HS1997 is based on the assumptions shown in the following three equations (see HS1997):

$$V_t = V_{t-1} + \alpha \cdot S/2 \cdot Q_{t-1} + \varepsilon_{t-1} \quad (1)$$

Equation (1) means that the unobservable fundamental value V_t equals the fundamental value V_{t-1} of the previous period plus the change in value $\alpha \cdot S/2 \cdot Q_{t-1}$ that is due to private information, reflected in the previous trade, plus the change in value ε_{t-1} that is due to public

⁵ It is also shown by (Kang and Ryu 2010) that the relation between trade size and information content depends on the way trade size is defined, and on whether a weighted or a normal average is used.

information. The component $\alpha \cdot S/2 \cdot Q_{t-1}$, where $S/2$ is the half spread and Q_t is a trade indicator, taking the value 1, if the trade was buyer initiated and -1 if it was seller initiated⁶, can be derived from the models by Copeland and Galai (1983) and Glosten and Milgrom (1985). Therefore, α is the proportion of the half spread due to asymmetric information.

$$M_t = V_t + \beta \cdot S/2 \sum_{i=1..t-1} Q_i \quad (2)$$

According to equation (2) the midpoint M_t of the bid-ask spread differs from the fundamental value by the cumulated inventory, i.e. the cumulated inventory on the respective day.⁷ If there were neither inventory costs nor private information the midpoint was equal to the fundamental value. Equation (2) is based on inventory theories of the spread (e.g. Ho and Stoll 1981) and means that liquidity providers adjust their midpoints on the basis of accumulated inventory in order to induce inventory equilibrating trades. Thus, β is the proportion of the half spread due to inventory holding costs.

$$P_t = M_t + S/2 \cdot Q_t + \eta_t \quad (3)$$

P_t is the quote on the market, and M_t is the observable midpoint between bid and ask price.

Equation (3) means that the HUF/EUR quote fluctuates around the midpoint by the half-spread, depending on whether we observe a buy or sell.⁸

Differencing equation (2) and substituting ΔV_t by its expectation $\alpha \cdot S/2 \cdot Q_{t-1}$ (equation 1) and substituting the whole expression into the differenced version of equation (3) leads then to a two-way decomposition by the following regression:

$$\Delta P_t = S/2 \cdot (Q_t - Q_{t-1}) + \lambda S/2 \cdot Q_{t-1} + e_t \quad (4)$$

Here ΔP_t is the price change between two subsequent trades. Equation (4) may therefore be interpreted as the (private) information that is potentially incorporated in the last trade. $S/2 \cdot (Q_t - Q_{t-1})$ is the price movement due to switches between buy and sell orders, thus a jump between the two edges of the spread, if a buyer initiated order is followed by a seller initiated order and vice versa. The joint effect of asymmetric information and inventory holding is

⁶ A trade is buyer initiated, if a buyer hits an existing limit sell order from the order book with a buy market order or by placing a limit buy order that is matched by the system with an active limit sell order.

⁷ Note that equation (2) assumes trades of the standard size one. Since on the HUF/EUR market 85% of all trades are of the minimum size of 1 million EUR this assumption seems to be justified.

⁸ The estimated spread does not necessarily equal the quoted spread (HS 1997). The difference with observed posted spreads is that the estimated spread reflects trades inside the spread but outside the midpoint.

captured by λ , and e_t reflects the arrival of public information. For details of the derivation see HS1997.

In a second step, an analysis for different trade sizes can be useful. To derive equation (4), the assumption, given by equation (3), was used. As trade size is not included in equation (3), it implicitly states that the spread is independent of the trade size. Explicitly considering trade size in all assumptions is thus necessary. For three size categories, this results in the following regression equation:

$$\begin{aligned} \Delta P_t = & (S^s/2) \cdot D^s(t) \cdot Q_t + (\lambda^s-1) \cdot (S^s/2) \cdot D^s(t-1) \cdot Q_t \\ & + (S^m/2) \cdot D^m(t) \cdot Q_t + (\lambda^m-1) \cdot (S^m/2) \cdot D^m(t-1) \cdot Q_t \\ & + (S^l/2) \cdot D^l(t) \cdot Q_t + (\lambda^l-1) \cdot (S^l/2) \cdot D^l(t-1) \cdot Q_t + e_t \end{aligned} \quad (5)$$

D_s is a dummy variable that equals 1 if the size of the trade falls in the “small” category and 0 when this is not the case. The same applies for D_m and D_l .

As equation (4) does not allow distinguishing between the inventory effect and the asymmetric information effect, Huang and Stoll suggest taking the potential serial correlation between trade flows into account. This three-way decomposition (for the derivation we again refer to HS 1997) is performed by simultaneous estimation of the following model:

$$E(Q_{t-1} | Q_{t-2}) = (1-2\pi)Q_{t-2} \quad (6)$$

$$\Delta P_t = S/2 \cdot Q_t + (\alpha+\beta-1) \cdot S/2 \cdot Q_{t-1} - \alpha \cdot S/2 \cdot (1-2\pi)Q_{t-2} + e_t \quad (7)$$

Here π is the estimated probability of a trade reversal. This probability is calculated using the potential serial correlation mentioned above. The model allows us to decompose the joint effect $\lambda = (\alpha+\beta)$ of asymmetric information (α) and inventory holding (β) into its components. Equations (4) and (6-7) serve as our baseline regressions in the subsequent analysis.

5. Empirical results

This section presents the results from the two-way and three-way decomposition of the spread on the Hungarian forint/ euro market in 2003-2004 as described above. All estimations are performed using the Generalized Method of Moments (GMM) of Hansen (1982) and the Newey and West (1987) correction of the covariance matrix for heteroscedasticity and autocorrelation of unknown form.

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The results for the basic two-way decomposition as in HS1997 are displayed in Table 2. The (estimated) average spread is 0.106 HUF for the whole sample period with the order processing component accounting for 42.58% of the spread and the sum of the adverse selection component and inventory holding component for 57.42%. The spread implies a revenue per one million euro round trade of roughly 420 EUR, which seems to be reasonable. From the most comparable study by McGroarty et al. (2007) revenues of about 44 to 206 EUR, depending on currency and sample period, can be derived. According to their results the revenues were highest on the EUR/JPY market in 1999 (206 EUR) and lowest for the DEM/CHF market (44 EUR) in 1998. The revenues on the EUR/USD were also quite small (between 69 and 75 EUR). The higher revenue on the HUF/EUR market is in line with the notion of a smaller market.

Applying the three-way decomposition from HS1997 the estimated spread is 0.107 HUF on average for the whole sample period. When we decompose the spread in three components by using equations (2) and (3), we find that the inventory holding costs account for 40.09% of the spread. The order processing costs account for 38.34% of the spread and the adverse selection costs for 21.57% of the spread (see Table 3).

Although the share of the inventory holding premium on the HUF/EUR market is of comparable size as found by McGroarty et al. (2007) for major markets, it should be stressed that it is larger in absolute terms, due to the larger spread on the HUF/EUR market. While according to their results the share of inventory effects in the total costs of a one million EUR round trade normally does not exceed 87 EUR⁹ we find costs of 168.38 EUR (40.09% of 420 EUR). Thus, inventory holding costs do play a prominent role on this market. This can be explained by the fact that we are dealing with a smaller and less liquid market. Additionally, this finding can be related to a higher prevalence of carry trading on the HUF/EUR market, due to the interest differential between both currencies during our sample period. Brunnermeier et al. (2009) provide extensive and convincing evidence of a higher currency crash risk for currencies involved in carry trading. They show that investment currencies are vulnerable to massive and sudden unwinding of carry trade schemes when the liquidity dries up for the carry-trade investors. They also find that insurance against downside risk becomes more expensive during and after this unwinding. For a trader this means that the inventory holding cost for HUF is higher than for currencies which are not involved in carry trades. Unfortunately we are not able to observe the share of carry trades in the total trading volume.

⁹ The only exception is the EUR/JPY in the post EMU sample with 134 EUR.

In order to check the robustness of these results the spreads are decomposed for two obvious subsamples, namely the trades executed in 2003 and the trades executed in 2004 (see Table 2). Starting again with the two-way decomposition the spread is estimated to be 0.133 HUF for 2003, whereas it declines in 2004 to 0.086 HUF. This decrease is statistically significant.¹⁰ The sum of the adverse selection and inventory holding component accounts for 56.43% of the total spread in 2003 and for 57.87% of it in 2004. Despite the slight relative increase for this combined component it lowers in absolute value with one third in 2004 compared to 2003. We performed the same analysis for each half year (See Table 2). Figure 1 visualizes the results of this analysis using the two-way decomposition. The estimated spread declines each half-year. This decline is statistically significant between the second half of 2003 – first half of 2004 and first half of 2004 – second half of 2004.

When we apply the three-way decomposition we again find the absolute spread to be decreasing each half year. This decrease is statistically significant between the second half of 2003 – first half of 2004 and the first half of 2004 – second half of 2004. The relative inventory holding component decreases quite strongly, especially over the last half year. The relative adverse selection component increases strongly over time: in the second half of 2004 it is almost twice as big as in the first half of 2003. The order processing cost, again, decreases as in the two-way decomposition.

Both approaches yield declining spreads over time. An explanation for this could be provided by the increased trading volume in the course of the deepening market over the sample period. In the two-way decomposition both components tend to decrease over time in absolute terms, whereas over the same period the average daily trading volume went up from 178.52 million euro in 2003 to 202.67 euro in 2004. This result is in line with theoretical models predicting that higher trading activity leads to lower spreads, since higher trading activity lowers waiting costs (Parlour 1998, Foucault et al. 2005, Rosu 2009).

On the level of individual spread components, theory suggests that there is a direct negative effect of the trading volume on the order processing component and the inventory holding component (Stoll 1978).¹¹ In contrast, there is no direct relation between trading volume and the adverse selection costs, since in these models there is only a role for the

¹⁰ We verified the statistical significance of spread changes in this paragraph by doing a t-test on year-specific dummies in an adapted regression setup. In this case for example we estimated $\Delta P_t = S/2 \cdot (Q_t - Q_{t-1}) + S/2 \cdot (Q_t - Q_{t-1}) \cdot D_{2004} + \lambda \cdot S/2 \cdot Q_{t-1} + \epsilon_t$. A t-test on the coefficient of the dummy (here: D_{2004}) indicates whether the difference between both years is statistically significant.

¹¹ For the order processing component this is the consequence of the possibility to distribute the fixed costs over more trades. The inventory holding component decreases, because the time between two consecutive trades becomes shorter and the dealer can revert his position at lower risk.

proportion of informed traders in the market (Glosten and Milgrom 1985) and size of an individual trade (Easley and O'Hara 1987). In our three-way decomposition results we find each half-year an absolute decrease in inventory holding costs and order processing costs per unit traded (except for a minor increase in inventory holding costs in the second half of 2003), whereas we do not find a decrease in absolute terms of the adverse selection costs over time. In our data we find consequently support for the theoretical relationship between trading activity and the spread components. One should, however, note that there may be a bidirectional causality between trading activity and spread size, i.e. higher trading activity may lead to lower spreads, but lower spreads may also attract traders and therefore increase trading activity. Previous work on the Helsinki stock market dealt with this endogeneity and showed that the linkage can be significant in both directions, both economically and statistically (Linnainmaa and Roçu 2009). Addressing the endogeneity issue falls beyond the scope of the model we use in this paper. A second reason for the decrease of the spread may be the lower volatility throughout the year 2004. In contrast, 2003 was characterized by the turmoil on the HUF/EUR market, including the speculative attack against the forint in January, the shift of the band in June and the increase of the interest rate by the central bank in December (see Gereben and Kiss M. 2006). Still, this volatility effect would not be consistent with the decreasing absolute order processing component.

As an extension we verify the relation between spread and trade size, by performing the two-way decomposition for different trade sizes (equation 5). The information on the frequency of trades provided in Table 1 suggests that it is reasonable to split up the trades into trades of 1 million euro (the minimum trade size: small trades), trades exceeding 1, but less than 3 million euro (medium trades) and trades of 3 million euro or more (large trades). Small trades account for more than 80 per cent of all trades. Our results for the HUF/EUR market are presented in Table 2 and Figure 2. We find that the spread is significantly¹² and positively related to trade size. We verified whether the difference in spread size between the different trade size categories could be driven by the fact that large trades loose relative importance in 2004, when the overall spread size decreased on the market, by estimating trade-specific spreads for each year separately. The significant difference between the estimated spread on small and large trades remained. The estimated spread on large trades is, over the whole dataset, 32.35% higher than the spread on small trades. This difference is also economically

¹² After estimating equation (5) we performed a t-test on the coefficients of the size-specific dummies to check the significance.

significant.¹³ The positive relation we observe is consistent with what other authors find on the interbank market. (Osler et al. 2010).

From a theoretical point of view we would expect the share of the adverse selection component and inventory holding premium on the one hand and the order processing component on the other hand to evolve with trade size in opposite directions: one would assume that the sum of the inventory holding and the adverse selection component increases with the trade size, because large trades are more difficult to offset and potentially contain more information. In contrast, the order processing component is expected to remain constant in absolute terms, as the share of the fixed costs covered by a trade only linearly depends on the trade size. This is also what we find in the data: while there seems to be no relation between trade size and the absolute size of the order processing component, we find a strong positive relation between trade size and the sum of the absolute adverse selection and inventory holding component. So, the order processing cost is indeed fixed per unit traded, whereas the adverse selection and inventory holding component increases per unit with trade size. This results in relatively decreasing order processing costs with trade size, and relative increasing costs for the combined component of inventory and adverse selection costs.

Table 4 summarizes our results for the two- and the three-way decomposition in comparison with previous studies. Despite the different setups of the studies in terms of counterparties, trading mechanisms and sample periods we can draw some interesting conclusions:

Taking the two-way decomposition as a reasonable starting point (see Table 4a) the two studies on minor markets (Bjønnes and Rime 2005 and our study) find shares of the order processing costs of 50 and 43 % respectively, and are thus located at the upper range of estimates of the OPC. Interestingly the two estimates of higher shares of OPC are by McGroarty et al. (2007) on the DEM/USD and EUR/USD market respectively, thus the largest and most liquid FX market. However, one has to keep in mind that we are talking about relative shares. Since the spread is much bigger in minor markets in absolute terms, our 43% correspond with about 181 EUR, which exceeds the whole estimated spreads (consisting of all three components) for all currencies but the EUR/JPY in the post EMU sample of McGroarty et al. (2007).

The three-way decomposition allows a comparison of the results on the inventory holding and the adverse selection component. Table 4b shows the results of our study in comparison

¹³ If a trader sells 3 million Euros on the interbank market he would, on average, pay 603,97 EUR under the form of deviation from the midpoint if he submits three orders of one million each. If he submits one large order he would pay, on average, 799,13 EUR.

with results from previous empirical work. The early studies by Lyons (1995) and Yao (1997) find evidence for an inventory holding premium, but are less comparable (due to the sample period and/or the high share of customer trades). The more comparable analyses, however, still provide inconsistent results. While Mende (2005) and Bjønnes and Rime (2005) do not find any evidence for an inventory holding premium, McGroarty et al. (2007) find an inventory holding component of various size, between 37 and 56% for the pre-EMU sample, and between 42 and 70% for the post-EMU period. They also extensively discuss these differing results and trace them back to the differences in individual dealer's data and market wide data. Since our dataset is very similar and might even cover a larger share of the market (due to the absence of competing brokerage systems at that time), it is not surprising that our results corroborate with theirs, and provide additional evidence for the presence of an inventory holding premium.

Summing up, and taking into account the difficulties in comparing the various studies, we find an order processing component that is large in absolute terms, but also located at the upper range in relative terms compared to previous studies. Furthermore we find a substantial share of the inventory holding premium, which contradicts the recent studies by Mende (2005) and Bjønnes and Rime (2005), but is in line with the comparable study by McGroarty et al. (2007).

6. Concluding remarks

In this paper we apply the well established spread decomposition model by Huang and Stoll (1997) to a new and large dataset on the Hungarian forint/ euro market. The main results are in line with existing studies on more liquid markets. Inventory holding costs account on average for 40% of the spread. Order processing costs and adverse selection costs represent on average respectively 38% and 21% of the spread.

Furthermore, we find that the increased trading volume that the market experienced during the transition process coincided with a decreasing spread size. In the end, adverse selection costs became more important. Order processing and inventory holding costs have declined over time.

Finally, we find a close relation between spreads and the order size: the spread considerably increases with order size. While the order processing component remains stable, the other components show a substantial increase.

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Summing up, our analysis confirms most of the results from previous theoretical and empirical studies, but also points at the differences between minor interbank market segments with low liquidity, competition and trading activity compared to major currency markets.

FIGURES

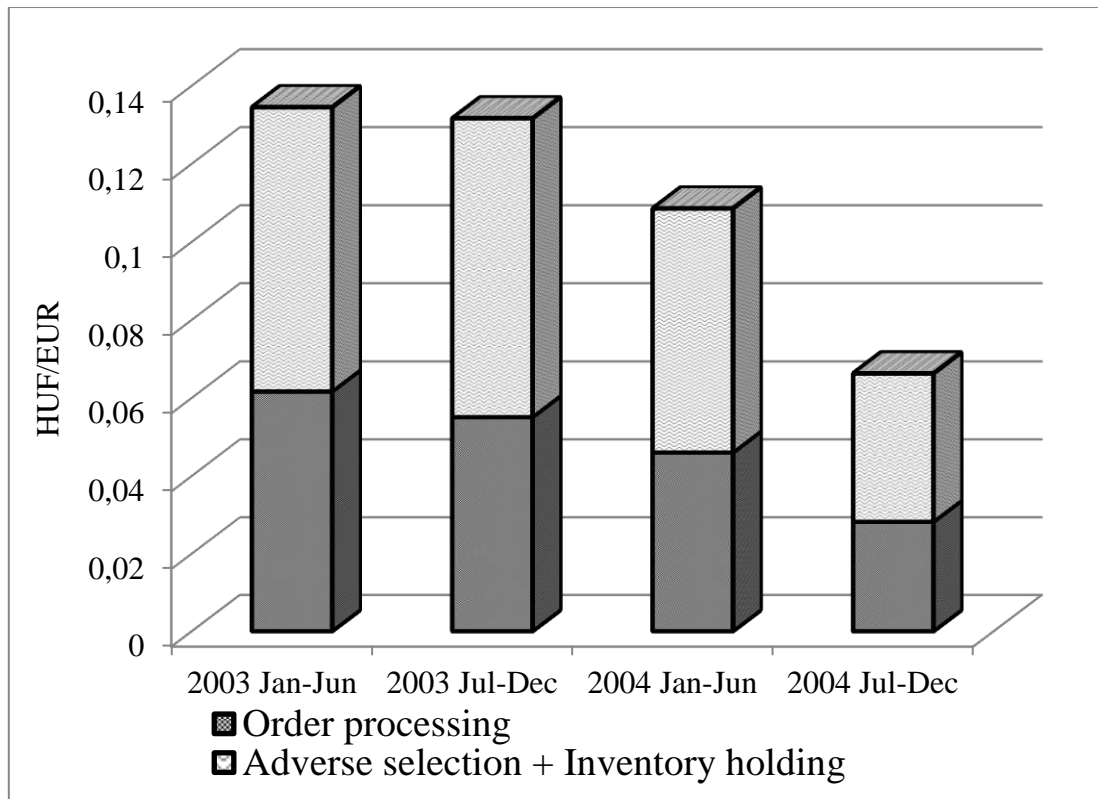


Figure 1: Decomposition by half-year.

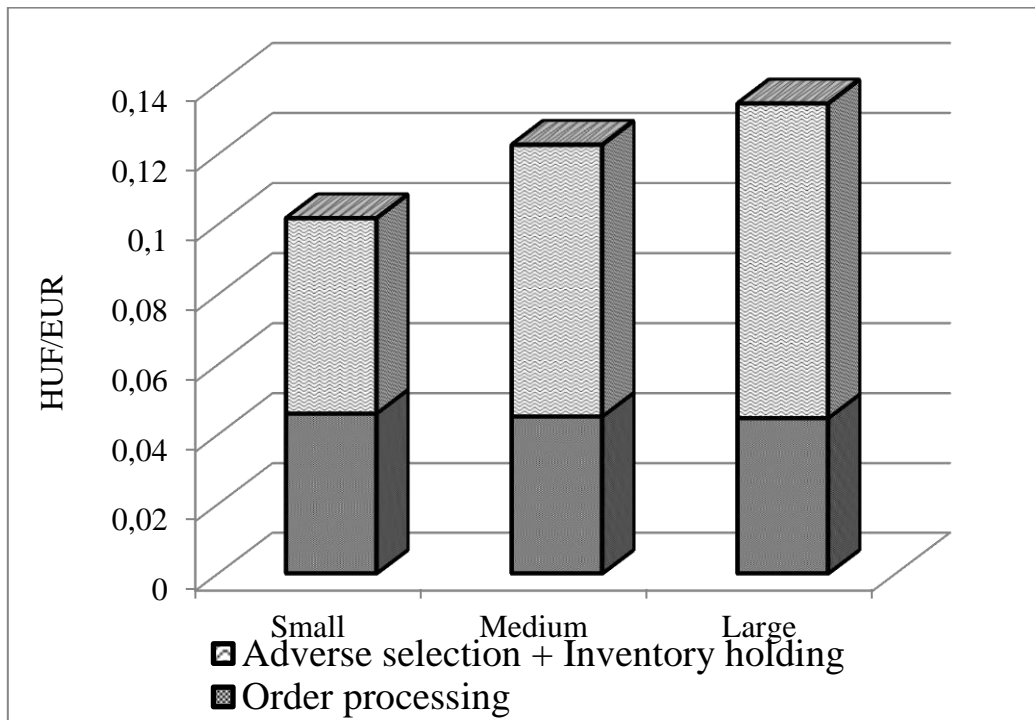


Figure 2: Decomposition by trade size.

TABLES

	Whole sample	2003	2004
Number of quotes	437,420	193,447	243,973
Number of trades ^{a,b}	72,622	31,978	40,644
Average trade size	1,304,398 EUR	1,339,827 EUR	1,276,523 EUR
Trades \leq 1 million €	80.38%	78.89%	81.55%
Trades >1 million € and <3 million €	13.79%	14.50%	13.23%
Trades \geq 3 million €	5.83%	6.61%	5.22%
Average number of quotes per day	881.90	806.03	953.02
Average number of trades per day	146.42	133.24	158.77
Average daily trading volume (million €)	190.98	178.52	202.67
Average spread (basis points) ^c	4.18	5.20	3.42

Table 1: Descriptive statistics of the dataset

^a The buy and sell are together counted as 1 trade; ^b On days with a minimum volume and during the office hours; ^c Estimated with the two-way decomposition

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	Half-Spread	λ * Half-Spread	R ²	Spread	ASC+IHC ^a	OPC ^b
Whole sample	0.053 (64.43) ***	0.031 (59.50) ***	0.10	0.106	0.061 57.42%	0.045 42.58%
2003	0.067 (48.31) ***	0.038 (41.55) ***	0.11	0.133	0.075 56.43%	0.058 43.57%
2004	0.043 (47.37) ***	0.025 (47.01) ***	0.10	0.086	0.050 57.87%	0.036 42.13%
2003 jan-jun	0.067 (29.58) ***	0.036 (24.87) ***	0.09	0.134	0.073 54.16%	0.062 45.84%
2003 jul-dec	0.066 (43.97) ***	0.038 (36.19) ***	0.13	0.132	0.077 58.15%	0.056 41.85%
2004 jan-jun	0.054 (31.98) ***	0.031 (33.58) ***	0.10	0.109	0.063 57.62%	0.046 42.38%
2004 jul-dec	0.033 (46.96) ***	0.019 (38.68) ***	0.13	0.066	0.038 57.41%	0.028 42.59%
	Half-Spread	$(\lambda-1)$ * Half-Spread	R ²	Spread	ASC+IHC ^a	OPC ^b
Small trades	0.051 (60.64) ***	-0.023 (-29.34) ***	0.10	0.102	0.056 54.80%	0.046 45.20%
Medium trades	0.061 (36.78) ***	-0.023 (-19.81) ***	0.10	0.123	0.078 63.23%	0.045 36.77%
Large trades	0.067 (30.75) ***	-0.022 (-13.35) ***	0.10	0.135	0.090 66.79%	0.045 33.21%

Table 2: Two-way decomposition of the spread.

^a Adverse selection component + inventory holding component (in absolute (HUF) and relative values); ^b Order processing component (in absolute (HUF) and relative values); *** indicates significance at the 1% level, t-values in parentheses

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	(1-2 π)	Half-Spread	($\alpha+\beta-1$) * Half-Spread	α * Half-Spread *(1-2 π)	π	Spread	OPC ^a	ASC ^b	IHC ^c
Whole sample	0.454 (136.36) ***	0.054 (89.34) ***	-0.021 (-31.98) ***	0.005 (8.74) ***	0.27	0.107	0.041 38.34%	0.023 21.57%	0.043 40.09%
2003	0.471 (94.70) ***	0.067 (61.35) ***	-0.027 (-22.77) ***	0.006 (5.09) ***	0.26	0.134	0.054 39.95%	0.024 17.65%	0.057 42.40%
2004	0.441 (98.38) ***	0.043 (67.51) ***	-0.016 (-23.47) ***	0.005 (7.83) ***	0.28	0.087	0.032 37.10%	0.023 26.32%	0.032 36.59%
2003 jan-jun	0.473 (66.42) ***	0.068 (38.50) ***	-0.029 (-15.30) ***	0.005 (2.88) ***	0.26	0.136	0.058 42.72%	0.021 15.83%	0.056 41.46%
2003 jul-dec	0.469 (67.50) ***	0.066 (50.20) ***	-0.025 (-17.37) ***	0.006 (4.57) ***	0.27	0.133	0.049 37.28%	0.026 19.42%	0.057 43.30%
2004 jan-jun	0.455 (70.13) ***	0.055 (45.97) ***	-0.021 (-16.22) ***	0.006 (4.68) ***	0.27	0.110	0.042 37.85%	0.025 22.40%	0.044 39.75%
2004 jul-dec	0.428 (69.14) ***	0.033 (56.53) ***	-0.012 (-19.62) ***	0.0045 (7.59) ***	0.29	0.067	0.025 36.87%	0.021 31.35%	0.021 31.78%

Table 3: Three-way decomposition of the spread.

^a Order processing component (in absolute (HUF) and relative values); ^b Adverse selection component (in absolute (HUF) and relative values); ^c Inventory holding component (in absolute and relative values); *** indicates significance at the 1% level, t-values in parentheses.

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	Market	Period	# obs.	Types of trades	CP ^a	Spread components		Market Fraction
						IHC+ASC ^b	OPC _b	
Minor markets								
This study	HUF/EUR	Jan 2003- Dec 2004 (2 years)	71,630	Complete trading on Reuters D3000	IB	57%	43%	Whole (electronic) market
Bjønnes/Rime (2005) ^c	NOK/DEM	Feb 1998 (5 days)	144	Direct and indirect trades	C+IB	50%	50%	Market maker, customer share of 18%
Major markets								
Lyons (1995)	DEM/USD	Aug 1992 (5 days)	838	Direct and brokered trades	IB	49%	51%	Large share of indirect trades
Bjønnes/Rime (2005) ^d	DEM/USD	Feb 1998 (5 days)	169-430	Direct and indirect trades	(C+)IB	81%	19%	One dealer, customer share of 3%
McGroarty et al. (2007)	USD/JPY	Aug-Sept 2008 (20 days)	399,124	Complete EBS trading	IB	72%	28%	Major fraction of electronic market
	USD/CHF		42,952			86%	14%	
	DEM/USD		484,005			56%	44%	
	DEM/JPY		128,064			91%	9%	
	DEM/CHF		73,898			74%	26%	
McGroarty et al. (2007)	USD/JPY	Aug-Sept 2009 (20 days)	225,825	Complete EBS trading	IB	64%	36%	Major fraction of electronic market
	USD/CHF		72,939			81%	19%	
	EUR/USD		310,300			45%	55%	
	EUR/JPY		42,743			79%	21%	
	EUR/CHF		29,654			67%	33%	

Table 4a: Comparison with selected previous studies (Two-way decomposition).

^a Counterparty: C = customer, IB = interbank; ^b IHC: inventory component, ASC: adverse selection component, OPC: order processing component; ^c Dealer 1 in the sample; ^d Dealer 3 in the sample, dealers 2 and 4 trade less in DEM/USD and are not considered here.

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	Market	Period	# obs.	Types of trades	CP ^a	Spread components			Market Fraction
						IHC ^b	ASC ^b	OPC ^b	
Minor markets									
This study	HUF/EUR	Jan 2003- Dec 2004 (2 years)	71,630	Complete trading on Reuters D3000	IB	40 %	21%	38%	Whole (electronic) market
Bjønnes/Rime (2005) ^c	NOK/DEM	Feb 1998 (5 days)	144	Direct and indirect trades	C+IB	0%	49%	51%	Market maker, customer share of 18%
Major markets									
Lyons (1995)	DEM/USD	Aug 1992 (5 days)	838	Direct and indirect trades	IB	30%	15%	45%	Large share of indirect trades
Yao (1998)	DEM/USD	Nov-Dec 1995 (25 days)	4,518	Direct and indirect trades	C+IB	70%	23%	7%	High share of customer trades (75% of profits)
Mende (2005)	EUR/USD	Jul-Nov 2001 (87 days)	2,859	Direct and indirect trades	C+IB	0%	<40%	>60%	
Bjønnes/Rime (2005) ^d	DEM/USD	Feb 1998 (5 days)	169-430	Direct and indirect trades	(C+)IB	0%	72%	28%	Customer share of 3%
McGroarty et al. (2007)	USD/JPY	Aug-Sept 2008 (20 days)	399,124	Complete EBS trading	IB	43%	29%	28%	major fraction of electronic market
	USD/CHF		42,952			56%	29%	15%	
	DEM/USD		484,005			38%	25%	37%	
	DEM/JPY		128,064			50%	36%	13%	
	DEM/CHF		73,898			37%	45%	15%	
McGroarty et al. (2007)	USD/JPY	Aug-Sept 2009 (20 days)	225,825	Complete EBS trading	IB	61%	7%	32%	major fraction of electronic market
	USD/CHF		72,939			70%	17%	13%	
	EUR/USD		310,300			42%	9%	49%	
	EUR/JPY		42,743			65%	18%	16%	
	EUR/CHF		29,654			45%	33%	21%	

Table 4b: Comparison with selected previous studies (Three-way decomposition).

^a Counterparty: C = customer, IB = interbank; ^b IHC: inventory component, ASC: adverse selection component, OPC: order processing component;

^c Dealer 1 in the sample; ^d Dealer 3 in the sample, dealers 2 and 4 trade less in DEM/USD and are not considered here.

LIST OF REFERENCES

- Admati, Anat R. and Paul Pfleiderer (1988). Selling and Trading on Information in Financial Markets, *American Economic Review* 78, 96-103.
- Ahn, Hee-Joon, Bae Kee-Hong and Kalok Chan (2001). Limit Orders, Depth, and Volatility: Evidence from the Stock Exchange of Hong Kong, *Journal of Finance* 56, 767-788.
- BIS (1996). *Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity 1995*, Bank for International Settlements: Basel.
- BIS (2005). *Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity in 2004*, Bank for International Settlements: Basel.
- BIS (2010). *Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity in 2010*, Bank for International Settlements: Basel.
- Bjønnes, Geir Høidal and Dagfinn Rime (2005). Dealer Behavior and Trading Systems in Foreign Exchange Markets, *Journal of Financial Economics* 75, 571-605.
- Brunnermeier, Markus K., Stefan Nagel and Lasse H. Pedersen (2009). "Carry Trades and Currency Crashes." NBER Macroeconomics Annual 2008 23, 313-347.
- Chae, Joon and Albert Wang (2009). Determinants of Trading Profits: The Liquidity Provision Decision, *Emerging Markets Finance & Trade* 45, 33-56.
- Chen, Ho-Chyuan and Juping Wu (2009). Volatility, Depth, and Order Composition: Evidence from a Pure Limit Order Futures Market, *Emerging Markets Finance & Trade* 45, 72-85.
- Copeland, Thomas C. and Dan Galai (1983). Information Effects on the Bid-Ask Spread, *Journal of Finance* 38, 1457-1469.
- Ding, Liang (2009). Bid-Ask Spread and Order Size in the Foreign Exchange Market: An Empirical Investigation, *International Journal of Finance and Economics* 14, 98-105.
- Easley, David and Maureen O'Hara (1987). Price, Trade Size and Information in Securities Markets, *Journal of Financial Economics* 19, 69-90.
- Foucault, Thierry, Ohad Kadan and Eugene Kandel (2005). Limit Order Book as a Market for Liquidity, *Review of Financial Studies* 18, 1171-1217.
- Frömmel, Michael, Norbert Kiss M. and Klára Pintér (2011). Central Bank Communication, Macroeconomic Announcements, and Order Flow: An Analysis of the Hungarian Foreign Exchange Market, *International Journal of Finance and Economics* 16:2, 172-188.
- Frömmel, Michael, Alexander Mende and Lukas Menkhoff (2008). Order Flow, Private Information and Exchange Rate Volatility, *Journal of International Money and Finance* 27:6, 994-1012.
- George, Thomas J., Gautam Kaul and M. Nimalendran (1991). Estimation of the Bid-Ask Spread and its Components: A New Approach, *The Review of Financial Studies* 4:4, 623-656.
- Gereben, Aron and Norbert Kiss M. (2006). A Brief Overview of the Characteristics of Interbank Forint/Euro Trading, *Magyar Nemzeti Bank Bulletin*, December, 21-26.
- Glosten, Lawrence R., and Paul R. Milgrom (1985). Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders, *Journal of Financial Economics* 14, 71-100.
- Hansen, Lars P. (1982). Large-Sample Properties of Generalized Method of Moments Estimators, *Econometrica* 50, 1029-1054

- Hartmann, Philipp (1991). Trading Volumes and Transaction Costs in the Foreign Exchange Market, *Journal of Banking and Finance* 23, 801-824.
- Ho, Thomas and Hans R. Stoll (1981). Optimal Dealer Pricing under Transactions and Return Uncertainty, *Journal of Financial Economics* 9, 47-73.
- Huang, Roger D. and Hans R. Stoll (1997). The Components of the Bid-Ask Spread, A General Approach, *Review of Financial Studies* 10, 995-1034.
- Kang, Jangkoo and Doojin Ryu (2010). Which Trades Move Asset Prices? An Analysis of Futures Trading Data, *Emerging Markets Finance & Trade* 46, 7-22.
- Kyle, Albert S. (1985). Continuous Auctions and Insider Trading, *Econometrica* 53, 1315-1336.
- Lin, Chuang-Yuang, Ruey-Shan Wu and Tsai Chen (2010). Taiwan's Foreign Exchange Market – Volatile but Still Efficient? Evidence from Intraday Data, *Emerging Markets Finance & Trade* 46, 33-41.
- Linnainmaa, Juhani T. and Ioanid Rosu (2009). *Weather and Time Series Determinants of Liquidity in a Limit Order Market*, AFA San Francisco Meetings Paper
- Lyons, Richard K. (1995). Tests of Microstructural Hypotheses in the Foreign Exchange Market, *Journal of Financial Economics* 39, 321-351.
- Lyons, Richard K. (1998). Profits and Position Control: a Week of FX Dealing, *Journal of International Money and Finance* 17, 97-115.
- Lyons, Richard K. (2001). *The Microstructure Approach to Foreign Exchange*, Cambridge MA, MIT Press.
- Madhavan, Ananth and Seymour Smidt (1991). A Bayesian Model of Intraday Specialist Pricing, *Journal of Financial Economics* 14, 3-24.
- McGroarty, Frank, Owain ap Gwilym and Stephen Thomas (2007). The Components of Electronic Inter-Dealer Spot FX Bid-Ask Spreads, *Journal of Business Finance & Accounting*, 34:9&10, 1635–1650.
- Mende, Alexander (2005). *Order Flow Analyses and Foreign Exchange Dealing*, Peter Lang Publishing Group: Frankfurt am Main et al.
- Naik, Narayan Y., Anthony Neuberger. and S. Viswanathan (1999). Trade Disclosure Regulation in Markets with Negotiated Trades, *Review of Financial Studies*, 12, 873-900.
- Newey, Whitney K. and Kenneth D. West (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703-708.
- Osler, Carol L., Alexander Mende and Lukas Menkhoff (2010). *Price Discovery in Currency Markets*, *Journal of International Money and Finance*, forthcoming.
- Parlour, Christine A. (1998). Price Dynamics in Limit Order Markets. *Review of Financial Studies* 11, 789-816.
- Payne, Richard (2005). Informed Trade in Spot Foreign Exchange Markets: an Empirical Investigation, *Journal of International Economics* 61, 307-329.
- Rosu, Ioanid (2009). A Dynamic Model of the Limit Order Book. *Review of Financial Studies* 22, 4604-4641.
- Rime, Dagfinn (2003). E-Trading Systems in Foreign Exchange Markets, *New Economy Handbook*, Chapter 21, Elsevier Science, 469-504.
- Stoll, Hans R. (1978), The Pricing of Security Dealer Services: An Empirical Study of NASDAQ Stocks, *The Journal of Finance* 33:4, 1153-1172.

Chapter 3

- Stoll, Hans R. (1989), Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests, *The Journal of Finance* 44:1, 115–134.
- Stoll, Hans R. (2003). Market Microstructure, in: *Handbook of the Economics of Finance*, (edited by G. Constantinides, R.M. Stulz, and M. Harris), vol. 1, Elsevier Science, 553-604.
- Van Ness, Bonnie F., Robert A. Van Ness and Richard S. Warr (2001). How Well do Adverse Selection Components Measure Adverse Selection? *Financial Management* 30, 77-98
- Yao, Jian (1997) *Market Making in the Interbank Foreign Exchange Market*, Working Paper S-98-3, Stern School of Business, New York University.

Chapter 4

**Bid-Ask Spread Components on the
Foreign Exchange Market:
Quantifying the Risk Component**

Bid-Ask Spread Components on the Foreign Exchange Market: Quantifying the Risk Component*

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Abstract

We study the tightness of the complete electronic interbank foreign exchange market for the HUF/ EUR over a two year period. First, we review the cost components that a liquidity provider on this type of market faces, and integrate them in an empirical spread decomposition model. Second, we estimate the bid-ask spread components on an intraday basis, and find that order processing costs account for 47.09% of the spread and that, the combined inventory holding and adverse selection risk component accounts for 52.52% of the spread. In addition, we provide evidence for an endogenous tick size that accounts for one third of the order processing costs and we also estimate the number of liquidity providers based on the risk component. Third, we apply the model to some interesting spread patterns. Using our model we investigate the stylized difference in spreads between peak-times and non-peak times. We find that the combined compensation for inventory holding and adverse selection risk increases during non-peak times, particularly because the risk that a liquidity provider will have to carry an inventory overnight rises. Furthermore, we apply the model to the interesting spread pattern around a speculative attack. Here, credibility of the exchange rate band, competition amongst liquidity providers and increased volatility are key in understanding what happens during this episode of extreme turmoil.

JEL: F31, G15

Keywords: microstructure, foreign exchange, spread, Hungary, inventory, adverse selection, liquidity

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Bid-Ask Spread Components on the Foreign Exchange Market: Quantifying the Risk Component

1. Introduction

Liquidity captures how easy it is to convert an asset into cash, and is a key-variable of interest when investigating financial markets. Moreover, liquidity also determines the speed at which information about an asset can be processed and it as well affects the asset's expected return. From a society point of view, liquidity is important for the stability of the global financial system. In the literature, many different indicators are used to characterize the liquidity of a market. In fact, liquidity can be seen as a multi-dimensional variable: one can distinguish volume (how much trade there is on a market), depth (the quantity available on the market over different prices), immediacy (the speed at which an order can be executed), resiliency (the speed at which new orders enter the market if the quantity available on the market gets depleted) and tightness (the difference between what you pay when you buy an asset and what you get when you sell an asset).⁶⁰ In this work we focus on this last dimension – the tightness/ bid-ask spread – on a specific foreign exchange market. It is this bid-ask spread that is the cause of a difference between the price at which transactions take place and the theoretical mid-quote observed on the market. These costs are important for market participants and influence the price discovery process.⁶¹ We aim to contribute to the understanding of this liquidity dimension by investigating the link with the different types of costs that liquidity providers face.

From the first paper that introduced an early concept of market microstructure onwards (Garman (1976)), bid-ask spreads received a considerable amount of attention in what later became a distinct field of finance research.⁶² The price difference between bid and ask prices is in general treated as a compensation for the costs liquidity providers incur on the market. Their costs can be divided in three categories: order processing costs, inventory holding costs and adverse selection costs (Tinic (1972)). There exists a vast amount of work that tries to seize the importance of each of these components. Early structural models include (Ho and

⁶⁰ Concerning the definition of tightness, every transaction of course involves a buyer and a seller. To be more specific, the bid-ask spread is the difference between the price an active buyer pays and the revenue an active seller receives.

⁶¹ For the HUF/ EUR market, which represented in 2004 only 0.22% of the global turnover on the FOREX market, this cost sums up to 59.99 Million EUR in 2003 and 61.85 Million EUR in 2004.

⁶² In this early model, the spread emerged as a result of dealers who set optimal bid and ask quotes assuming that market activity follows a Poisson-process.

Stoll (1981); Huang and Stoll (1997); Stoll (1978)). Empirical models follow a somewhat different approach and do not impose a complete structural model that describes the trading process. They do not impose strong assumptions on the behaviour of traders and the way how they interact, but model each component separately and explicitly (the most notable example – that inspired us and to which we will refer a lot – being developed by Bollen, Smith and Whaley (2004)).

In this paper, we will apply an empirical spread decomposition model to a very extensive dataset on Hungarian forint/ euro interbank trading for 2003 and 2004. The Hungarian forint was traded exclusively vis-à-vis the euro during this sample period (trades from other currencies took place by using the euro as vehicle currency). The HUF/ EUR is a minor market, which accounted for 0.22% of the global turnover in 2004 (BIS (2004)), and according to the latest record accounts for 0.4% of the global turnover (BIS (2010)). An interesting characteristic of the HUF/ EUR market is that there was a strong liquidity increase/ transaction cost decrease over the sample period. This strong liquidity variation over a relatively short amount of time is the result of an integration process, and distinguishes this foreign exchange market from others.

A typical feature of the interbank foreign exchange market that we study, is that it has no designated market makers. Still, attracted by potential profits, some participants can play the role of liquidity provider. This leads to the emergence of what has been labelled endogenous liquidity provision in theoretical, experimental and empirical work (Anand and Venkataraman (2013); Bloomfield, O'Hara and Saar (2005)). For the same HUF/ EUR market, and using the same data, it was argued that endogenous liquidity providers were active around jumps (Frömmel, Han and Van Gysegem (2013)).

The contribution of this paper is at least threefold. First, we provide results of an empirical spread decomposition model for the foreign exchange market. Although the literature refers often to insights from the empirical spread decomposition model, results for this type of model are relatively scarce. Full results are currently only available for Nasdaq stocks. Our work allows to review the impact on the results of the very different microstructure of this type of market (e.g. specialists vs. endogenous liquidity providers). Second, we apply the model on an intraday, hourly basis. This frequency is more in line with the frequency at which liquidity provision takes place. An additional advantage is that the intraday pattern is not averaged out. Furthermore, we take the partly fixed and partly variable nature of order processing costs into account. Third, we provide some interesting applications of this type of models: we look to the stylized intraday spread pattern from a cost component perspective

and we apply the model to a period of major turmoil on the market (i.e. a speculative attack against the Hungarian forint).

2. The foreign exchange market: characteristics and advantages

The foreign exchange market is the largest financial market in the world: the daily turnover of the global foreign exchange spot market was for 2010 estimated at \$ 1.5 trillion (BIS (2010)), which is approximately 15 times the global GDP that is generated on a daily basis.⁶³ In addition to its overwhelming size, the foreign exchange market has some other distinctive features. First of all, the market has a two-tier structure. One tier consists of trade between customers and banks. The customers are then the actual end-users of the currencies and can be further split up in non-dealer financial institutions on the one hand (such as hedge funds) and corporations and governments on the other hand (such as importing and exporting firms). However, also retail investors and algorithmic traders represent an increasing amount of the trading activity (King, Osler and Rime (2011)).⁶⁴ A second tier consists of interbank trading. It is in this second tier that the price formation takes place and where the spot exchange rates are set. These spot exchange rates are the reference prices for all other foreign exchange deals (e.g. on the dealer-customer market). A second distinctive feature of the foreign exchange market is that it is a decentralized market (without designated market makers). It is an electronic, order-driven market where participants can trade by posting a market order or a limit order. A market order is immediately matched with the best available outstanding order at the opposite side of the book. Limit orders stay in the book until they are matched with an incoming market order or until they are cancelled by the participant who placed the order. A third distinctive feature is that there are no official opening and closing times (in principle, there are trades 24h a day except for the weekends).

The foreign exchange market has advantages over other markets for microstructure researchers. First of all, trading is really continuous as it is not interrupted by specific opening/ closing procedures and/ or batch auctions that lead to breaks in the timeseries. Secondly, many participants have access to this market, and they can all observe all outstanding buy and sell orders in the marketplace (there is no hidden liquidity, like iceberg orders etc.). It is therefore often argued that the foreign exchange market is the real-world

⁶³ Assuming on average 20 working days per month. The Worldbank estimates the global GDP for 2010 at \$ 63 trillion.

⁶⁴ Their share in trading on the overall foreign exchange market has risen from 20% in 1998 to more than 50% in 2010.

market that resembles perfect competition most closely. This is in line with the assumptions behind most models in microstructure research, and makes the interpretation of our results less ambiguous. The specific dataset we are working with offers additional advantages: it is a very complete dataset (we cover all electronic trading of this currency pair), and it has an unusually long time span of two years. These characteristics ensure the representativeness and robustness of the results we obtain, and allow us to investigate the variation over time.

3. Cost components of the bid-ask spread

The bid-ask spread is the source of revenues for liquidity providers. However, providing liquidity also comes with a cost. The first to categorize these costs was Tinic (1972). He identified three broad cost components, and his categorization was the starting point for an extensive literature that deals with the theoretical modelling of these costs and testing their empirical relevance.

Order processing costs (OPC)

The first category concerns the general costs of providing market making services. These costs are partly fixed (e.g. wages of traders, floor space rent, subscriptions to trading platforms and information providers,...). These fixed costs have to be covered while providing liquidity, and can be spread over all transactions of the liquidity providers. Another part of the order processing costs is variable and thus incurred each time there is a trade (e.g. exchange, clearing and settlement fees, attention by traders,...). The fact that part of the order processing costs is variable has implications for the spread and price dynamics.⁶⁵

Inventory holding costs (IHC)

Secondly, providing liquidity implies that you take positions and hold an inventory. This inventory is unwanted in the sense that a liquidity provider does not want to be exposed to price movements. Theoretical models predict that this results in a process in which liquidity providers adapt their spread based on their inventory of risky assets. They change their quotes in order to induce inventory equilibrating trades (Amihud and Mendelson (1980); Ho and Stoll (1981)). In addition to the risk of an adverse price movement, holding an inventory also

⁶⁵ For variable order processing costs and an interesting model dealing with the implications for price dynamics, see p.101-106 of Foucault, Thierry, Marco Pagano, and Ailsa Röell, 2013, Market liquidity: Theory, evidence and policy, (Oxford University Press, USA).

comes with an opportunity cost for the funds invested in the inventory, as this inventory needs to be financed on a continuous basis (Demsetz (1968)).

Adverse selection costs (ASC)

Thirdly, there is also a cost associated with engaging in a transaction with a market participant who has superior information. The first to analyse the asymmetric information problem for a dealer when she has to decide on the bid and ask quotes was (Bagehot (1971)). A formal treatment of this problem involves splitting up the market participants looking for execution into two categories, based on their motivation: informed traders, who have private information on the real value of the underlying quote, and uninformed traders (Glosten and Milgrom (1985)). This last category was initially considered to trade for liquidity reasons or to hedge themselves. Later, another type of traders was added: traders who think they have private information without actually having it. This subcategory can then be labelled as noise traders.⁶⁶ Both informed and uninformed traders pay the spread in order to get executed. The informed traders know, however, that when selling (buying), the bid (ask) quote they get (pay) is too high (low), and does not correspond to the true, underlying value. Liquidity providers only know that this type of traders exists, but cannot know in advance whether a specific trade is liquidity or information motivated. This leads to a problem of adverse selection, and liquidity providers will ask a compensation for the associated risk. While Glosten and Milgrom (1985) treat this problem in a quote driven framework where traders arrive sequentially, Kyle (1985) models this problem in an order driven framework, similar to a batch auction. This last setting is more similar to the foreign exchange market.

As a clarification, adverse selection costs are not linked to the presence of information per se in the market. When the information is symmetric, there will be no adverse selection cost for the liquidity provider. The risk of new, symmetrically spread, information disclosed after the transaction and leading to price movements is fully contained in the inventory holding costs.

4. Model

Above we outlined the theoretical foundations for the main cost categories that liquidity suppliers face when they want to add liquidity to the book. In this chapter we will follow the literature in assuming that the spread is a function of these three cost components:

⁶⁶ For an extensive discussion that clarifies the difference between these different types of traders (which are used in many cases interchangeably), see Bloomfield, O'hara and Saar (2009).

$$SPRD_i = f(OPC_i, IHC_i, ASC_i) \quad (\text{Eq. 1})$$

We now develop an empirical spread decomposition model and focus on how to model each cost component.

Order processing component

Because of their partly fixed nature, order processing costs are expected to be negatively related to the volume traded. Empirical work found evidence for this negative relation between some measure of volume traded and the spread (Bollen, Smith and Whaley (2004); Branch and Freed (1977); Harris (1994); Stoll (1978); Tinic (1972); Tinic and West (1972); Tinic and West (1974)). However, volume traded also carries information. When splitting up the volume traded in an expected and an unexpected component, one could argue that unexpected deviations from normal intraday trading volume point at private information, and consequently push the exchange rate up or down. This was confirmed in various empirical studies (Danielsson and Payne (2011); Easley and O'Hara (1992)). This substantial part of the volume traded will by consequence rather be related to private information, and not to order processing costs. Additionally, it has been noted that the relation between volume traded and spread could be obfuscated by the fact that participants are active on multiple markets over which they can distribute their fixed costs. Moreover, above we referred to the notion that not all costs of order processing are fixed: some of them are incurred each time there is a trade. We include this in our model as a constant that is not depending on the volume traded.

Following the insights on the nature of order processing costs (partly variable, partly fixed) and the nature of volume traded (partly expected, partly unexpected) we model the OPC as partly fixed and partly depending on the expected volume traded. Here we differ from Bollen, Smith and Whaley (2004). This specification is consistent with a broad definition of order processing costs, which includes clearing and settlement fees, tick-size and non-competitive rents.⁶⁷ All these costs have in common that they are covered by revenues under the form of a mark-up (partly a mark-up per trade, and partly a mark-up over all expected trades per interval) on top of the risk components. The resulting order processing costs per time-interval are consequently modelled as:

⁶⁷ A separate variable indicating the level of competition, such as the modified Herfindahl index, would make it possible to split this component further up. This data is, however, not available. For an extensive analysis of the link between competition and bid-ask spreads on this type of markets, see Huang and Masulis (1999).

$$OPC = \alpha_0 + \alpha_1 Exp TV_i \quad (\text{Eq. 2})$$

With OPC being equal to the order processing cost and EXP TV being equal to the expected volume traded.

Risk component

The notion that liquidity providers are aware of the risk of adverse changes in the price of assets in their inventory (inventory holding costs) was tested empirically in the literature using various proxies for these price changes. A logical class of proxies for price movements that can be easily transferred to the foreign exchange market are volatility-related proxies. For different markets, a positive relation between volatility and bid-ask spreads was reported (Bollerslev and Melvin (1994); Branch and Freed (1977); Harris (1994); Stoll (1978); Tinic (1972)).

The presence of asymmetric information (adverse selection costs) in a market is, because of its very nature, difficult to detect for market participants and researchers. Early ex post proxies on equity markets included inter alia the number of specialist stocks in which a certain market maker was active (Tinic and West (1972)) and trading volume over market capitalization (Stoll (1978)). On the foreign exchange market different adverse selection proxies were used. Some authors used quoting frequency on the Reuters EFX system (Phylaktis and Chen (2010)). The more active in quoting on Reuters, the more informed a bank seems to be. Related to this, the size of the counterparty (Bjønnes, Osler and Rime (2008)) was also shown to be related to private information. These authors find that large traders are the most informed (and connect in that way with what Stoll (1978) found for the equity market). Another, interesting approach consists of looking to the price impact (Menkhoff and Schmeling (2010)). Using an extensive inter-dealer FX trading dataset with counter-party identities, it has been shown that orders by counterparties who have superior information have a greater price impact (Moore and Payne (2011)). Finally, asymmetric information was also found to be related to order flow characteristics. Theoretical models have shown that information enters the market when informed participants take liquidity, rather than when participants add liquidity (Evans and Lyons (2006); King, Sarno and Sojli (2010)). Additionally, when dealers think they have information (e.g. after accepting a large order from a financial institution on the customer-side) they are found to take liquidity in the direction of the information (Bjønnes, Osler and Rime (2008); Osler, Mende and Menkhoff

(2011)). In a next stage, it is widely documented that, because of their (private) information content, order flow drives the price in the spot FX market (Evans and Lyons (2002)).

In general terms, one can treat this two risk components in one common framework. The compensation required by the liquidity provider for taking the inventory holding and the adverse selection risk after accommodating, for example, a sell order will be equal to the expected loss when the quote moves adversely times the probability of an adverse quote movement:

$$RISK = -E(\Delta S \mid \Delta S < 0) \cdot \Pr(\Delta S < 0) \quad (\text{Eq. 2})$$

Bollen, Smith and Whaley (2004) show that the expected cost of accommodating an order can be quantified as the price of an at-the-money option with the time that the stock is held in inventory as expiration. This finding is very intuitive: such an option would yield a pay-off structure that is compensating the loss when the price of the asset in inventory changes adversely. For example, if a liquidity provider has no inventory and is accommodating an active buy (sell) order, she will be short (long) the asset. A call-option (put-option) will hedge her position. The midquote immediately prior to the submission of the active order will be the true price. This will also be the strike. The combined inventory holding and adverse selection costs (the risk component) will thus be equal to an at-the-money option. The value of this option is given by (Black and Scholes (1973); Merton (1973)):

$$RISK = S[2N(0.5\sigma\sqrt{t}) - 1] \quad (\text{Eq. 3})$$

With S being equal to the true price, here the midquote, σ being equal to the annualized standard deviation of the return, t being equal to the time between two offsetting trades expressed in years, and $N(\cdot)$ is the cumulative standard normal density function. This formula is identical for valuing an at-the money call option and an at-the-money put option.

Bollen, Smith and Whaley (2004) further explore the effect of a stochastic time between offsetting trades and also the effect of taking into account that the combined, hedged position of the liquidity provider still makes it possible to profit from advantageous price changes. They conclude that under realistic parameter settings, both features only have a minor effect on the calculated risk component.

Formally, we can now combine the cost components mentioned above in a regression model:

$$SPRD_i = \alpha_0 + \alpha_1 Exp TV_i + \alpha_2 RISK_i + \varepsilon_i \quad (\text{Eq. 4})$$

With $SPRD$ is the observed intraday spread, $Exp TV$ is the expected volume traded and $RISK$ is the premium for the combined inventory holding and adverse selection risk.

5. Empirical results

5.1 Data

In this work, we use an unusually rich and complete tick-by-tick dataset for the years 2003 and 2004. Our dataset consists of all quotes, i.e., limit and market orders, on the HUF/EUR interbank market that have been placed via the Reuters D3000 broking system. This was the only platform that offered services for this currency pair during our sample period, so we cover the complete electronic trading. We observe the price, the quantity in euro that was offered or asked, whether it was a market or a limit order and the exact time when the order was placed and when it disappeared. We observe whether the order was withdrawn or whether it was executed, i.e., matched with another limit or market order. We use the data to reconstruct the limit order book at the intraday level. This allows us to determine the mid-quote and the quoted spread at any point in time. We aggregate the tick-by-tick data and information from the reconstructed limit order book (both at market event frequency) to twelve hourly observations per day (from 7am till 7pm). This way, we obtain 6060 hourly intervals which cover the hours with the highest market activity (See Figure 2 for the intraday distribution of ticks, which is a measure for how active traders are).

The quote and the volume traded over the two years contained in our dataset are shown in Figure 1. An important event clearly stands out: there was a speculative attack against the top of the currency band in January 2003, followed by a central bank intervention which brought the quote back to its target value. Table 1 presents some summary statistics.

5.2 The bid-ask spread and its determinants

In this work we focus on the quoted spread, as this is the relevant spread for a market participant who is looking for execution.⁶⁸ Interdealer bid-ask spreads on currency markets

⁶⁸ Some works, especially dealing with stock market spreads, focus also partly (or fully) on the effective spread (being the difference between the price at which a transaction takes place and the prevailing quote from the other side of the book). These authors typically find that the effective spread is smaller than the quoted spread (i.a. Bollen, Smith and Whaley (2004)). This is possible because in some markets, participants can negotiate directly for a better quote, or because there is hidden liquidity available in the book. In our market, negotiations are not directly observed and there is no hidden liquidity. Therefore, the effective spread will be at least as high as the

are in general low. They range from roughly 0.5-2 basispoints on liquid markets to 40 basispoints on less liquid markets (King, Osler and Rime (2011); Osler, Mende and Menkhoff (2011)).⁶⁹ We see that for our market the half-year average quoted spread lies between 0.25 HUF/ EUR and 0.39 HUF/ EUR. This corresponds to respectively 9.99 and 15.01 basispoints. We distinguish for each interval the time-weighted spread and the last spread observed in the book.⁷⁰

The volume traded per hourly interval is expressed in million EUR. The minimum size of a trade is 1 million EUR, and all quantities traded are multiples of this minimum size. Most of the trades, 80.38%, that take place actually have the minimum size, 13.79% of the trades are for 2 million EUR and the remaining 5.83% are for at least 3 million EUR. The fact that trades for the minimum size dominate is consistent with a widespread use of order splitting strategies by traders (in an attempt to minimize the market impact, see also Kyle (1985)). The average expected volume traded increased each half year from 7.58 million EUR to 12.08 million EUR per hourly interval

The volatility is calculated as the annualized standard deviation over the last 30 ten minutes intervals, such that it reflects the volatility over a frequency that is relevant for liquidity suppliers. The distribution of these volatilities is right-skewed. The time between trades is expressed in minutes, assuming that the volume traded during each interval is evenly distributed during the interval. When used to calculate the option value, the time between two trades is annualized.

5.3 Intraday patterns

As we undertake an intraday analysis, we are automatically concerned about the intraday pattern that characterizes our variables. Therefore, we calculate for the two-year sample period the intraday pattern for the bid-ask spread and the quantity traded, which can be found respectively in Figure 3 and Figure 4.⁷¹ The spread pattern is U-shaped. This contrasts to the W-shaped pattern found for the USD/ DEM spot market (Danielsson and Payne (2011)), but is consistent with what other authors found for a wide array of foreign exchange markets (McGroarty, ap Gwilym and Thomas (2009)). The intraday volume pattern is found to be M-

quoted spread (it will be higher if the order walks up the book). We focus by consequence only on the quoted spread.

⁶⁹ Although we should keep in mind that this is still very liquid compared to stock markets. The spread on Nasdaq stocks found by Bollen, Smith and Whaley (2004) corresponds to respectively 203.68, 108.67 and 61.88 basispoints for selective months.

⁷⁰ The time-weighted spread is calculated by multiplying each observed quote during an interval with the relative time it was observed.

⁷¹ These patterns were obtained using the median, and not the mean, to increase robustness.

shaped. This result is consistent with what other authors found for the foreign exchange market (Danielsson and Payne (2011); McGroarty, ap Gwilym and Thomas (2009)), but differs from the widely documented U-shaped pattern on other financial markets. We will use the pattern of the quantity traded as proxy for the expected quantity traded, in order to determine the order processing component. To take changing expectations into account, the pattern of expected trading volume is updated every half-year.

5.4 Results

Bivariate correlations

As a first step, we analyse the bivariate correlations between the variables we will use in the regression analysis (See Table 3). The correlations of all explanatory variables with the time-weighted quoted spread are significant at the 1% level.⁷² The correlations with the non-time weighted quoted spread are consistently lower (and unexpected trading volume becomes even insignificant). The large difference in correlations underlines the importance of choosing the right spread variable. The input variables used to quantify the risk component have at the individual level a lower correlation with the spread (23% for volatility and 38% for the time between two trades) than the correlation between spread and the modelled component (which is 56%). The correlation between the spread and the expected quantity traded has the right sign.

In a similar analysis for a set of liquid currencies (the currency pairs consisting of USD, JPY, CHF and EUR (DEM)), a very low correlation between the bid-ask spread and the volatility (1%-9%) was found (McGroarty, ap Gwilym and Thomas (2009)). The low results were, according to the authors, evidence for the hypothesis that liquidity provision on the foreign exchange market is very different from stock and bond markets, as no inventory needs to be managed (McGroarty, ap Gwilym and Thomas (2006)). Our results challenge this hypothesis. Possible reasons for our different results include that the results in the former work were obtained using the last quotes for each interval and not the time-weighted quotes, and that we are dealing with a less liquid currency for which the inventory risk is obviously bigger.

⁷² We use a t-test, with $t = \frac{\text{correlation} \sqrt{\text{number of observations}-2}}{\sqrt{1-\text{correlation}^2}}$.

Decomposition results

In Table 4 we present the results for the intraday empirical spread decomposition model for the whole sample period and for each half-year separately.⁷³ The intraday pattern, used to discriminate between expected and unexpected values is updated each half-year. All coefficients have the expected sign, and the coefficients on the order processing component and risk component are always statistically significant. In order to verify the validity of the model, we compare the explanatory power with that of a specification in which the spread is regressed on the input variables to our model, in an ad hoc specification (See Table 5). The R-squared for this specification is considerably lower, and the components are more difficult to interpret. This underlines the value added of the model in understanding the drivers of the bid-ask spread. When comparing the intraday explanatory power of our model with the interdaily analysis by Bollen, Smith and Whaley (2004) on the stock market, we see that it performs slightly weaker, with an R-squared in the range of 30.85%-40.95% where they have an R-squared of 54.40%-80.22% using a similar specification for selective months. They also run an ad-hoc specification, which has an R-squared in the range of 36.99%-57.68%. For the pink sheet market, and using daily data, a linear ad hoc model that incorporates the most-cited explanatory variables for spreads is found to yield an adjusted R-squared of 56% (Bollen and Christie (2009)).⁷⁴ The lower explanatory power for our market could be the result of a lower degree of efficiency in the behaviour of liquidity providers for this minor market, in comparison with the NASDAQ market which is widely followed and has designated market makers.

When we look at the size of the individual cost components, we find that the order processing component accounts on average for 47.09% of the intraday spread. This is in line with other order processing cost estimates for the foreign exchange market using theoretical spread decomposition models: 51% for the NOK/ DEM market (Bjønnes and Rime (2005)), 45% for the DEM/ USD market (Lyons (1995)) and 38% for the HUF/ EUR market using a theoretical model for the same sample period (Frömmel and Van Gysegem (2012)).

We defined the order processing component broad, so that it also includes tick-size. A distinct characteristic of the foreign exchange limit order book we are dealing with is the very low, seemingly irrelevant, tick size. In fact, quotes can in theory be submitted at a resolution

⁷³ We verified whether the results we obtain are possibly spurious by performing an Augmented Dickey-Fuller test on the timeseries of the variables. We can conclude that there is no such risk. Additionally, the value of the Durbin-Watson statistic on the residuals was always found to be bigger than the R-squared of each individual regression.

⁷⁴ Pink Sheet stocks do not need to meet certain minimum listing standards, and are traded over-the-counter. As such, information on these stocks is not always available. Stocks are not listed on this market, only quoted.

up to 0.0001 HUF/EUR. In that sense, tick size could be thought of as being a negligible part of the order processing component. However, if we look to the quotes submitted to the limit order book, the possibility to enter quotes up to such a high resolution is not used by market participants. We rather see the emergence of an endogenous tick size (Bollen and Christie (2009)). Figure 5 shows the distribution of all best quotes in the book during the two sample years over their first decimal number. We see that quotes like x.4xxx and x.6xxx are less prevalent than x.5xxx, and that quotes like x.9xxx and x.1xxx are less prevalent than x.0xxx. Thus, participants seem to round their quotes at the first decimal level. Figure 6 shows the same distribution for the second decimal. Here it is very clear that the quotes are strongly concentrated on x.x0xx and x.x5xx. Although there is no relevant exchange-mandated tick-size, 0.05 HUF/ EUR emerges as an endogenous tick size (roughly one third of the order processing component). This reflects that the low tick-size is not considered to be optimal. In this context, the tick size does not need to be interpreted as a cost, as is done in some other works, but rather as a (fixed) source of revenues for the liquidity provider.

The expected volume traded is very significant, both in economical and statistical terms. We find that if the expected volume traded is 10% higher (which corresponds to roughly one extra trade at the minimum size above the average), the spread is c.p. 4.50% lower.

We pointed out earlier in this work that liquidity providers will value the risk associated with adding liquidity to the book. We find that our modelled risk component accounts on average for more than half of the spread (52.52%), and is highly significant throughout the half-year periods.⁷⁵ So, the combined inventory holding and adverse selection risk clearly explains to a large extent the intraday bid-ask spread. The average volatility throughout the dataset is 5.25%. When the volatility is one standard deviation higher, the spread will c.p. be 62.74% higher. We see that the low spread in the last half year (23.90% lower than the two-year average) is caused by a decrease of the risk component: both the size of the costs and the reaction to this cost by the liquidity providers went down. The smaller size of the cost was at its turn caused by a very low volatility and a below average time between two trades.

Bollen, Smith and Whaley (2004) further use the option approach to isolate the adverse selection component. They argue that the relevant option will be out-of-the-money when

⁷⁵ We verified the robustness of the size of the option component by using a more advanced option valuation method that takes the presence of jumps into account. We therefore apply Merton's mixed jump-diffusion model (Merton, 1976) and use the jump characteristics for this market as reported in Frömmel, Han and Van Gysegem (2013). For the whole sample period, we find that the R-squared only increases slightly (from 34.69% to 34.77%). The risk component becomes slightly more important, and explains in this case 55.81% of the spread instead of 52.52%. The effect remains similar over various subsamples.

providing liquidity to an uninformed trader, with the bid (ask) as the strike price for the put (call) option when the liquidity provider accommodates a market sell (buy) order, and the mid-quote as true price. The relevant option will be in-the-money when dealing with an informed liquidity taker with, again, the bid (ask) as the strike price but a true price that is lower (bigger) than the bid (ask) of the put (call) option. This approach, which is very interesting from a conceptual point of view, comes however with a lot of uncertainty. Obviously, the magnitude of the difference between the bid/ ask price and the true price is unknown. Therefore, Bollen, Smith and Whaley (2004) compare this specification for a range of deviations and conclude, based on the explanatory power of the model, that it is most likely between 9% and 12%. Whilst keeping the additional uncertainty in mind, we followed an identical approach. Independent of the deviation we do not find a significant effect, both statistically and economically.

Our results for this further decomposition thus differ from the results for the same dataset when applying a structural spread decomposition methodology. Using this methodology it was found that although it is the smallest cost component, adverse selection costs still account for 21% of the spread (Frömmel and Van Gysegem (2012)). Bollen, Smith and Whaley (2004) also find clear evidence for an adverse selection component. The difference with their results could lie in the very different market microstructure on the market they study: on the NASDAQ, liquidity is provided by designated market makers (specialists), whereas on our market liquidity is provided endogenously. It could be that this type of liquidity providers does not price adverse selection separately (or to a lesser extent), because the amount of adverse selection on this market is low or because it is difficult to detect. However, as noted above the further decomposition of the risk component comes with a lot of additional uncertainty. Our results could in that sense just be an illustration of this uncertainty.

Estimate for the number of liquidity providers

The valuation of the risk component requires information on the time between two trades (See eq. 3). In our dataset we observe all trades together, and are not able to see how long the time between two trades is for an individual liquidity provider. Consequently, we used the average time between two trades as indicator for the time the currencies stay in the inventory of the liquidity provider. Still, the number of liquidity providers active on the market is unknown, but is likely to be higher than one. In that sense, our calculated risk premium is underestimating the risk premium an individual liquidity provider faces: she will have to wait longer before her unwanted inventory is matched with another order. Bollen, Smith and

Whaley (2004) show that in these circumstances the number of liquidity providers can be estimated from the data. They argue that in the regression that combines all cost components, the coefficient on the risk component should be one, as liquidity providers are perfectly hedged against this premium. If we then set this coefficient equal to one, we can estimate the length of the holding period:

$$SPRD_i = \alpha_0 + \alpha_1 Exp TV_i + RISK_i(t) + \varepsilon_i \quad (\text{Eq. 5})$$

With $SPRD$ is the observed intraday spread, $Exp TV$ is the expected volume traded, $RISK$ is the modelled combined inventory holding and adverse selection premium and t is the time between trades.

The estimate for the number of active liquidity providers can be easily calculated: the coefficient $\widehat{\alpha}_2$ from equation 4 can be used as a scaling factor for the average square root of the time between trades. We follow this approach and find that the estimated number of active liquidity providers is 15 for the whole sample period, 27 for the first half of 2003, 10 for the second half of 2003, 17 for the first half of 2004 and 7 for the second half of 2004.⁷⁶ The variation over the sample is quite large. The very high number in the first half of 2003 can be explained by the speculative attacks (cf. supra) and the turmoil on the market. We distinguish two different views on the link between the turmoil on the market and the number of liquidity providers we find to be active, depending on how liquidity providers perceived the credibility of the exchange rate band. If they considered the band to be very credible, it was a very interesting time to provide liquidity as they took a very low risk in terms of adverse price changes (which is basically what the inventory holding cost is about). It can be that this made that more market participants were actively providing liquidity, attracted by the low risk. They later left when the price risk increased again. Alternatively, if they considered the band to be not credible they could have been worried about the risk of big price shifts once the exchange rate breaks through the band. This makes that the inventory holding cost estimate that we obtained using the option model is too low (as the expected volatility was not equal to the ex post measured volatility). The high coefficient on the cost component is in that case not due to a higher number of liquidity providers, but rather to a cost estimate that is not in line with the perceived cost by liquidity providers in the market.

⁷⁶ Assuming, naively, that all liquidity are equally actively involved in adding liquidity to the book.

6. Applications

The model we developed and used above allows us to analyse the tightness on an intraday basis. In this section we will use it to investigate two interesting spread patterns: the stylized intraday pattern in tightness, and the remarkable spread pattern around a speculative attack against the HUF.

6.1 *Peak vs. non-peak times*

A first application of the model deals with the analysis of spread components during “peak” and “non-peak” times. It is a well-known fact that many variables related to the activity on a financial market follow an intraday pattern (See for our market Figure 3 and Figure 4). While our results were obtained with data for the most active trading hours (7am till 7pm), there still is a considerable amount of variation in activity over the hours included in our dataset. Based on the intraday distribution of the number of ticks, we are able to define “peak” and “non-peak” times (See Figure 2). We see that from 3pm onwards the activity starts to decline drastically. We will use this as cut-off point, and we will have by consequence 8 intervals per day during peak times and 4 during non-peak times (which results in 4040 observations during peak-times and 2020 observations during non-peak times).

If we look at the difference in spread, there is – as expected – a considerable difference between peak and non-peak times (during non-peak times the spread is more than double as high, see Figure 3). The average spread over the whole sample period during peak times is 0.23 HUF/ EUR, while during non-peak times it is 0.51 HUF/ EUR. Furthermore, we investigate whether this stylized pattern has any relation with the cost components, and if there is a relation, which cost components are responsible for these distinct bid-ask spreads. For this purpose we introduce a dummy variable for non-peak intervals in the model we applied earlier. The results can be found in Table 6. A first important finding is that compared to peak-times and controlling for the lower volume traded, both constituents of the order processing component are not significantly higher during non-peak times. For the risk component, the picture is different: this component is significantly (in both statistical and economical terms) higher during non-peak times (the coefficient is more than twice as large, the absolute size of the component is almost four times as large). Clearly, both the cost estimate itself and the sensitivity to changes in the calculated cost went up. Taking into account the different behaviour of liquidity providers during non-peak times versus peak-times increases the explanatory power of the model slightly (the R-squared goes from 34.54% to 38.11%).

The total size of the risk component consists of the calculated option premium and its coefficient in the intraday spread regression. First, we elaborate on the causes of the increase in the calculated size of the risk component during non-peak times. There we see that is not the volatility that increased during non-peak times (in fact, over the whole sample period it goes even down from 5.60% during peak times to 4.54% during non-peak times). It is rather the time between two trades that goes up from 9.31 minutes on average during peak-times to 37.80 minutes on average during non-peak times.

Second, we found that the sensitivity to changes in the calculated size of the cost component increases during non-peak times. Obviously, the increasing time between two trades still underestimates the increase in actual risk during non-peak times. At the end of the trading day, it is not only the time the liquidity provider expects her currencies to stay in her inventory that increases. There are two additional costs, which are both related to the risk that the liquidity provider has to keep her position overnight, and will have to wait till the next day in order to unload her inventory. One cost element of holding the inventory overnight is that there is the risk of bigger (adverse) price changes by the time that she starts to trade again the next day. A second element is that she will have to pay an overnight interest rate. Our findings can be related to earlier work that showed that dealers on the foreign exchange market try to end the day (and a fortiori the week) with an empty inventory (Bessembinder (1994); Huang and Masulis (1999)). It is argued for that matter that this effect is stronger on the foreign exchange market than on the stock market (Bjønnes and Rime (2005)).

6.2 Speculative attacks

In the data section we referred briefly to the speculative attack against the stronger edge of the Hungarian forint band in January 2003. At this time, the official exchange rate band of the Hungarian central bank was between 234.69 HUF/ EUR and 317.52 HUF/ EUR (276.10 HUF/ EUR \pm 15%). In 2002, the government demand increased by 4% of the GDP, which was higher than expected. In the same year, also the wage growth increased more than expected. Both events did put the HUF/ EUR target under pressure. After the referendum on EU enlargement in October 2002, the upward pressure on the HUF/ EUR quote increased even more, because international investors were demanding long-term government securities (convergence trades). Shortly after New Year 2003, there was a growing belief amongst market players that the central bank would have to abandon the exchange rate target. Hedge funds were trying to force a further appreciation of the forint. The central bank, however,

intervened on 15 and 16 January 2003, and bought 5.2 billion EUR on the market. After this intervention, the quote moved back inside the band.

We are interested in what role (endogenous) liquidity providers played before, during and after the speculative attack. More specifically we will use the methodology outlined above to analyse the spread set on the market. Figure 9 shows the evolution of the volume traded and the average time-weighted bid-ask spread in a three week timeframe around the speculative attack. We see a very large variation in the bid-ask spread during this timeframe. Interestingly, we find the spread to be gradually decreasing before the attack. The mean spread in the week before the attack was on average 0.13 HUF/ EUR while the average over the whole first half-year of 2003 was 0.32 HUF/ EUR. The attack impacts the quoted spread drastically, and in the week after the attack it is on average 0.53 HUF/ EUR. The build-up towards the attack should have been accompanied by uncertainty about the HUF/ EUR quote, and in that sense the unusually low spread prior to the attack is difficult to understand. Also, the unusually high spread after the attack could have multiple causes. We will investigate them below.

In order to understand how the liquidity provision was impacted by the attack, we apply the model for the three weeks around the attack. We recalculate the coefficients on each component for each week, which allows us to get a precise view on how the behaviour of liquidity providers changed during our timeframe.⁷⁷ The results can be found in Table 7. Prior to the speculative attack, the absolute order processing component has approximately the same size as the usual order processing component (in this paragraph, we use – given the variation of the results over time (cf. supra) – as usual the average result for the first half-year of 2003). They are respectively 0.1020 HUF/ EUR and 0.1123 HUF/ EUR. So, the low spread clearly stems from a lower risk component which is in absolute size 87.75% lower than usual. Both the value of the cost and the sensitivity to this cost are drastically lower (respectively 67.75% and 62.01% lower). This makes sense if we take into account that when the price is close to the strong band, it can only move in one direction as long as the band is maintained. It is clear that liquidity providers at this stage were not questioning the credibility of the band, and were considering the risk of adverse price changes to be much lower than usual.

In the week of the speculative attack, the spread rises with 42.85%. Still, the absolute order processing component decreases by 52.84%. Possible reason could here be that more

⁷⁷ Here we made the trade-off between having more robust estimates but neglecting the changing dynamics in the weeks around the attack when choosing for longer periods and having not enough observations to draw reasonable conclusions from our regressions but having a potentially more detailed view on the dynamics when opting for shorter periods.

participants start to follow the market very closely in the run-up to the attack. The increased competition that results from this erodes the fixed component of the spread (which also contains competitive rents, as argued earlier in the paper). Here the absolute size of the order processing component (0.0481 HUF/ EUR) becomes even slightly smaller than the endogenous tick size we found (0.05 HUF/ EUR). Key to understanding what drives the spread is here, again, the risk component: both the sensitivity to the cost and the cost itself increase greatly (respectively by 131.00% and by 128.68%). The increase in sensitivity can be linked to the increased competition that already affected the order processing component (when more liquidity providers are active, the difference between the average time between two trades on the market and the average time between two trades for an individual liquidity provider becomes bigger). The increase in the cost itself stems from the very high volatility during this week. The combined effect makes that the risk component is more than four times larger than the risk component in the week before the attack.

In the week after the attack, the spread is more than three times higher than in the week before this extreme event. Clearly, the fact that the attack actually happened made the market less tight and therefore illiquid, even if the central bank intervened successfully directly after the attack. The higher spread after the attack stems from an increase in both the order processing and the risk component compared to the pre-attack week. The order processing component and sensitivity to the order processing cost increased. Both could be explained by reduced competition after the attack. Additionally, the calculated risk component also went up by 353.49%. This is clearly the effect of the unusually low volatility that has been replaced by unusually high volatility. The sensitivity to the risk component almost doubled compared to the pre-attack week: now the quote can again move in two directions (as it shifted inside the band). Consequently, accommodating orders becomes more risky for liquidity providers, and they do ask a compensation for this.

Using the weekly coefficients, we also calculate the estimated daily spread components during the three weeks around the attack. Figure 10 shows the resulting components and the observed spread per day. We see that the model is able to track the day-to-day dynamics of the quoted spread. Figure 10 further illustrates how the order processing costs and risk component are driven by conditions on the market (number of liquidity providers/ competition, (un)certainty, market activity), and how this is directly reflected in the quoted spread.

7. Summary

In this work, we applied an empirical spread decomposition model to the HUF/ EUR market. Our data covers the complete electronic interbank market –where the price formation takes place– for a timespan of two years. We use intraday data coming from a tick-by-tick database and the reconstructed limit order book.

We examine the costs of providing liquidity in this type of market, and briefly summarize how these costs are treated in related literature. In a second step, these costs are quantified and the model is applied. We find that order processing accounts for 47.09% and the combined risk component accounts for 52.52% of the quoted spread. Over our sample period, we see a considerable amount of variation in their size. Although there is no exchange-mandated tick size, we do find evidence for an endogenous tick size of 0.05 HUF/ EUR. This tick size represents roughly one third of the order processing costs. The combined inventory holding and adverse selection risk is modelled as an option, and the costs are sized using option valuation. We can confirm that the option based model performs better than an ad hoc specification. We also find that the sensitivity of liquidity providers to the option value varies over time. We can partially explain this variation by a changing number of liquidity providers. When we try to split up the risk component further into a separate inventory holding and adverse selection component, we cannot find evidence for adverse selection. This is in contrast with existing NASDAQ results.

We further examine two interesting cases. During non-peak times, the spread is more than twice as high as during peak times. We use our model to investigate this discrepancy in more detail, and find that it is especially a higher risk component that is the cause. When we elaborate on this, we see that the average time between two trades increases but that liquidity providers are also concerned about the risk that they will have to carry their unwanted inventory overnight.

We also detect an interesting spread pattern around a speculative attack. As a second application, we study the dynamics of the cost components around this attack. We find an extremely high willingness to provide liquidity prior to the attack which results from the low risk component prior to the attack. During the attack, the risk component obviously increases and the order processing costs go down, which could be the result of increasing competition amongst liquidity providers. After the attack and the intervention by the central bank spreads rise massively. Now, both components go up: order processing costs rise again, and a strong increase in volatility makes that the inventory holding costs go up.

Chapter 4

Overall, this paper demonstrates the relevance of an option based spread decomposition approach for understanding how liquidity is provided on an interbank foreign exchange market. An interesting avenue for further research would be to employ data at the level of individual liquidity providers to study the heterogeneity amongst them and measure the ex post risk of holding an inventory. These findings could then further be integrated in a refined model of liquidity provision.

FIGURES

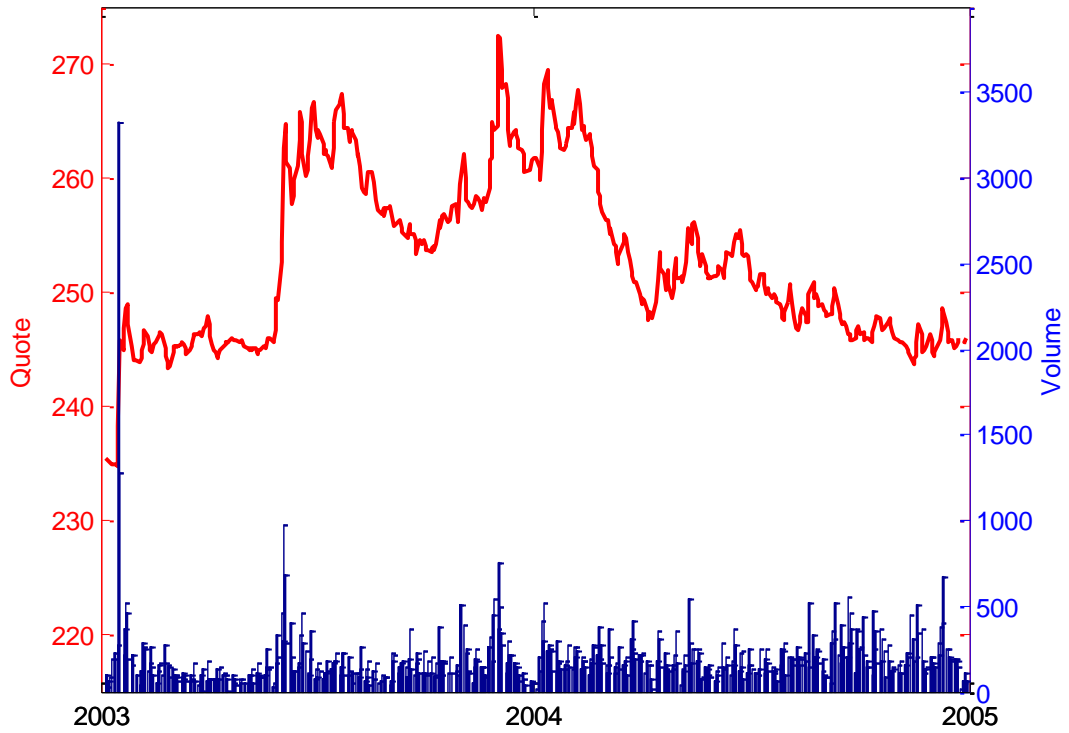


Figure 1: Average daily quote and total volume traded over the sample period

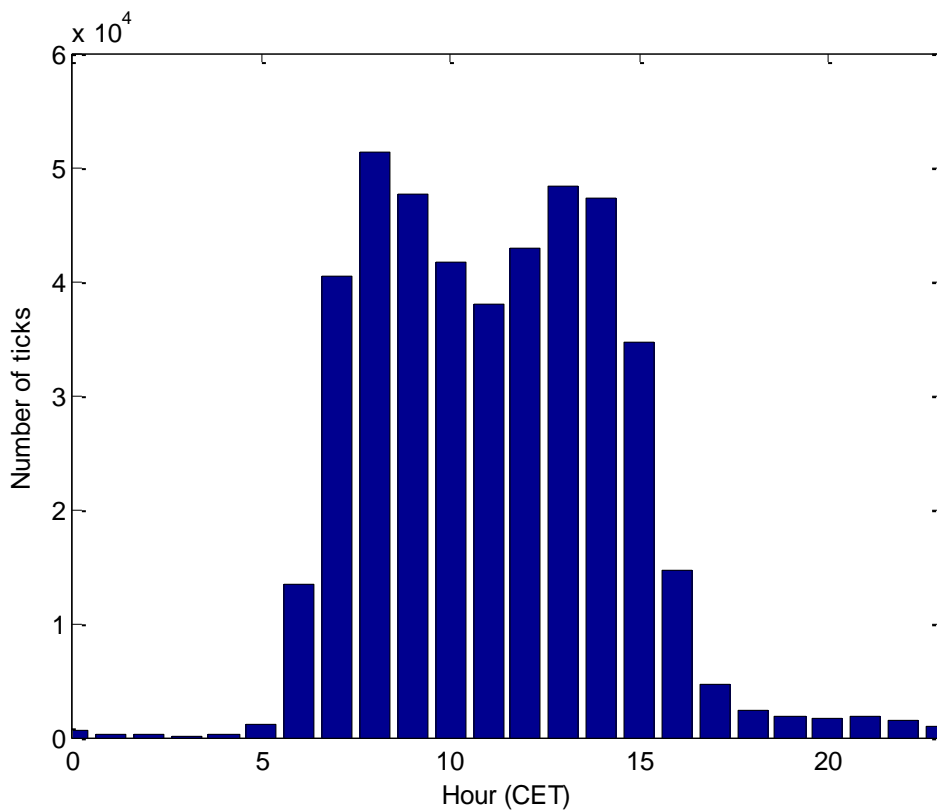


Figure 2: Number of ticks per hour (CET).

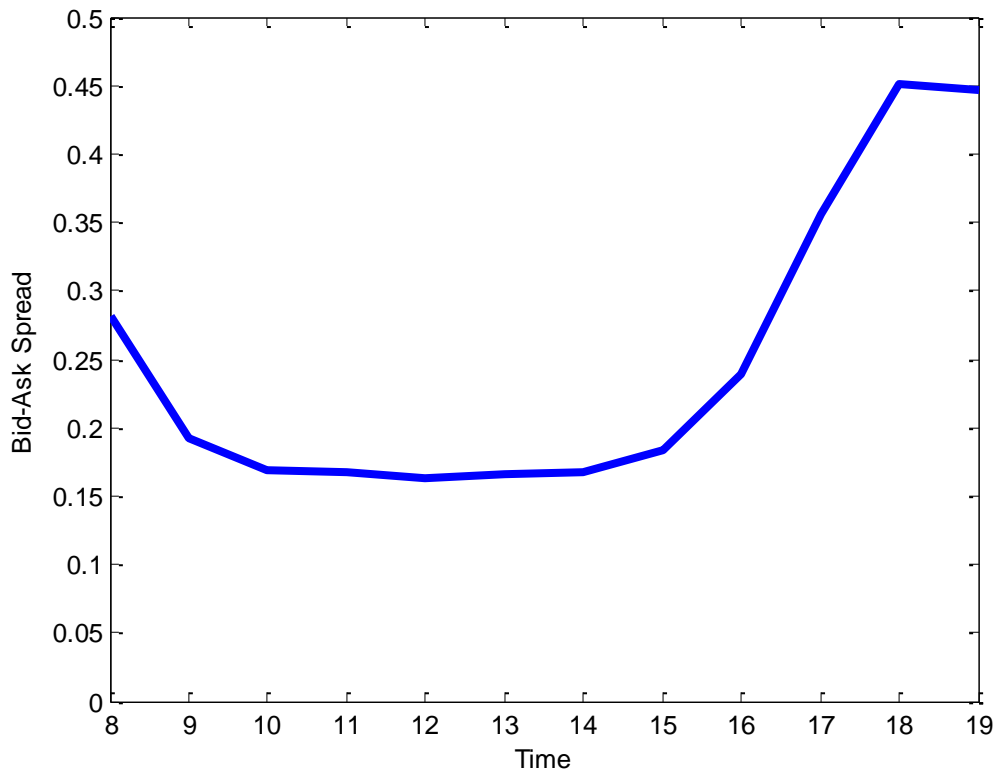


Figure 3: Expected bid-ask spread (HUF/ EUR; Intraday median)

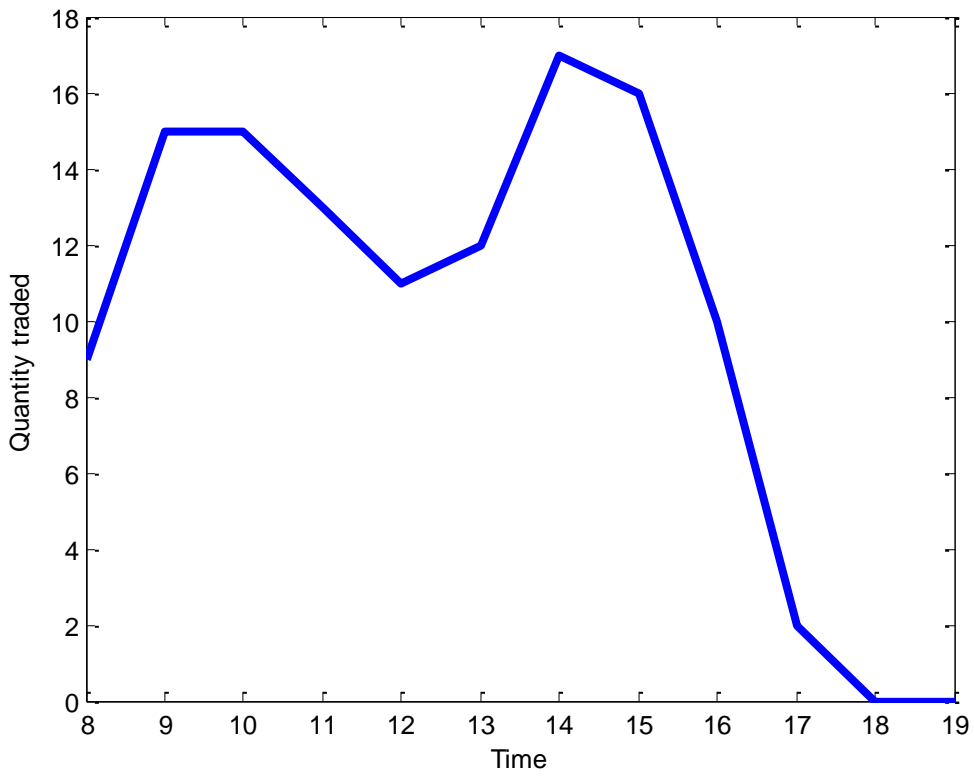


Figure 4: Expected quantity traded (Mill HUF; Intraday median)

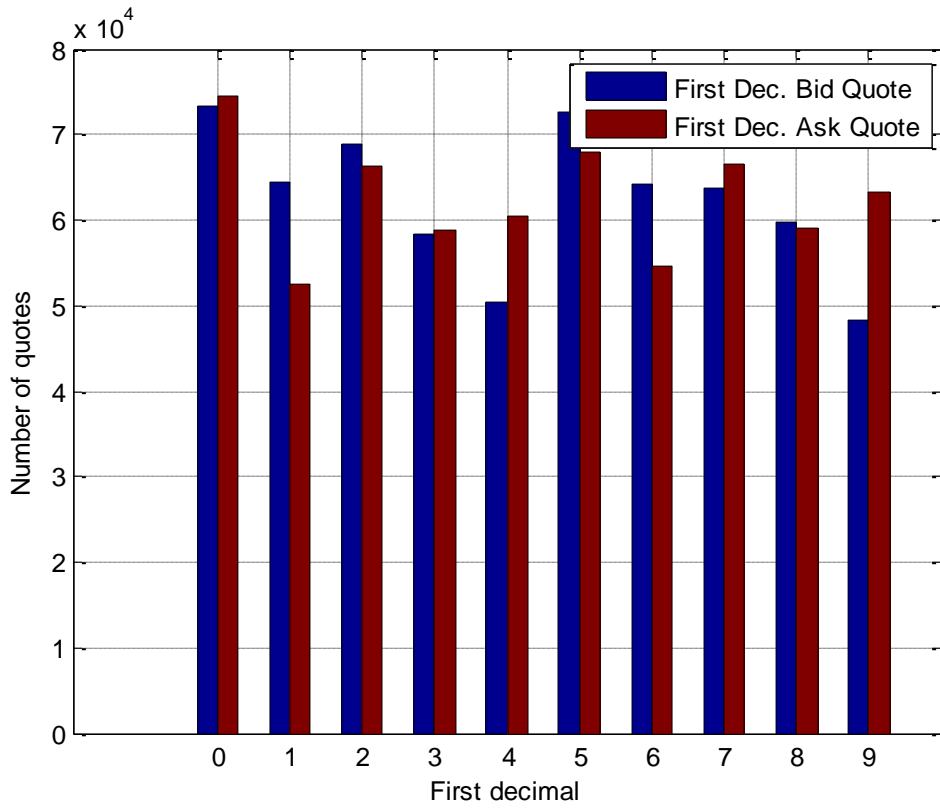


Figure 5: First decimal number of best bid/ best ask (HUF/EUR)

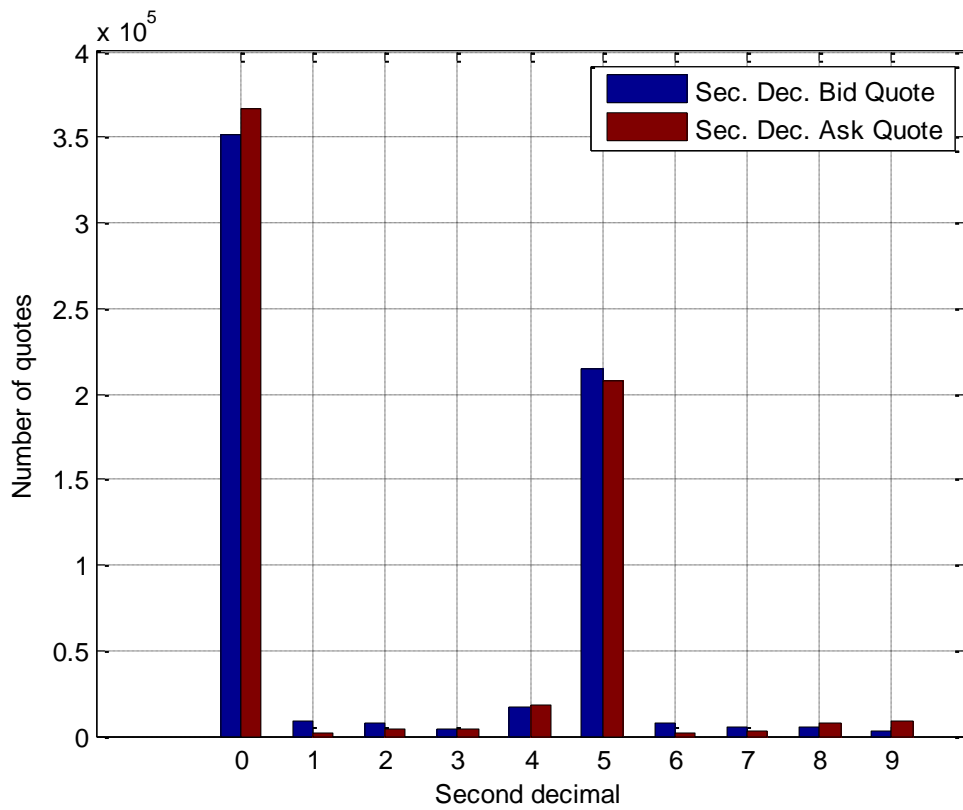


Figure 6: Second decimal number of best bid/ best ask (HUF/ EUR)

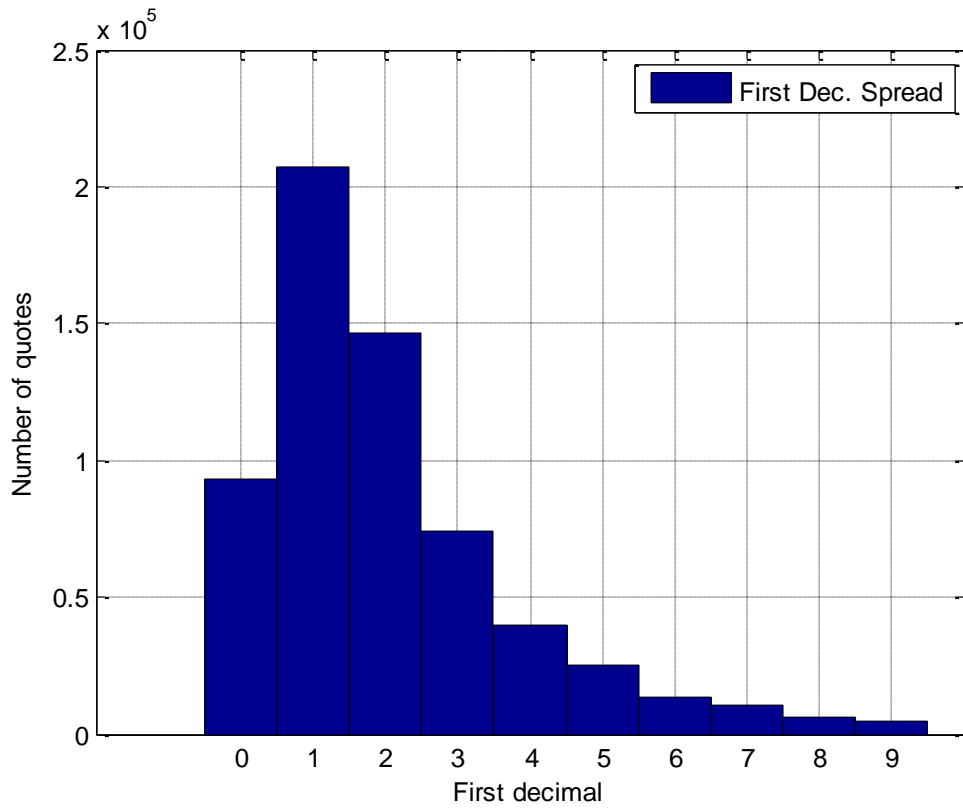


Figure 7: First dec. bid-ask spread (HUF/ EUR)

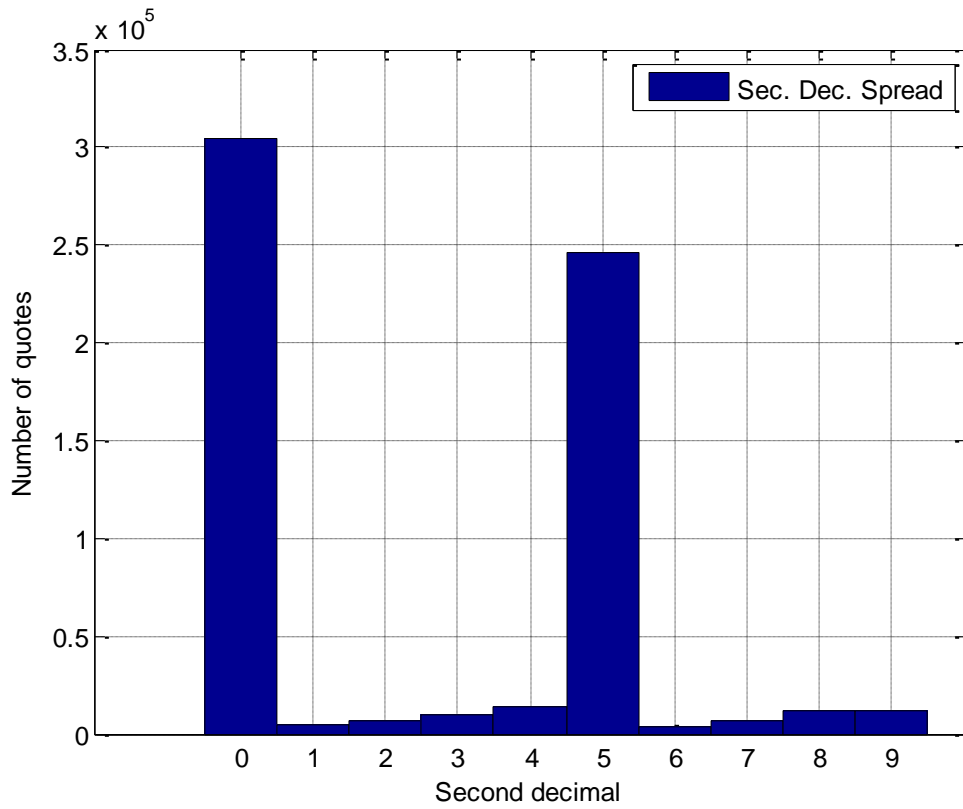


Figure 8: Second dec. bid-ask spread (HUF/ EUR)

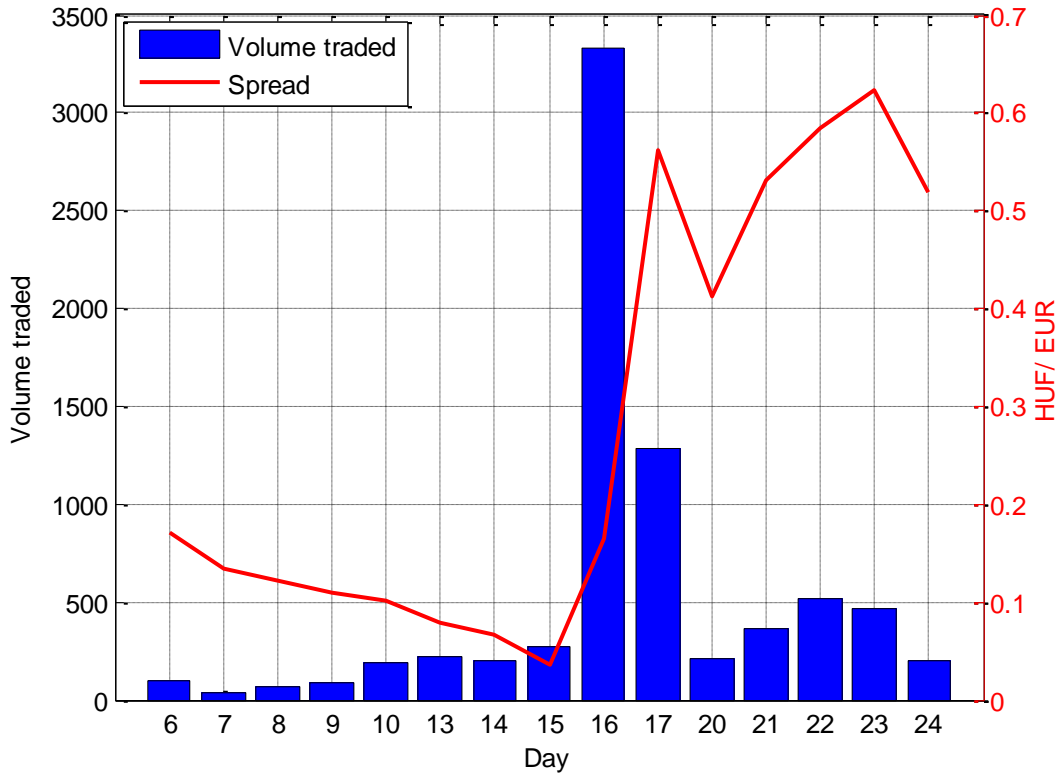


Figure 9: Spread and volume traded around the speculative attack

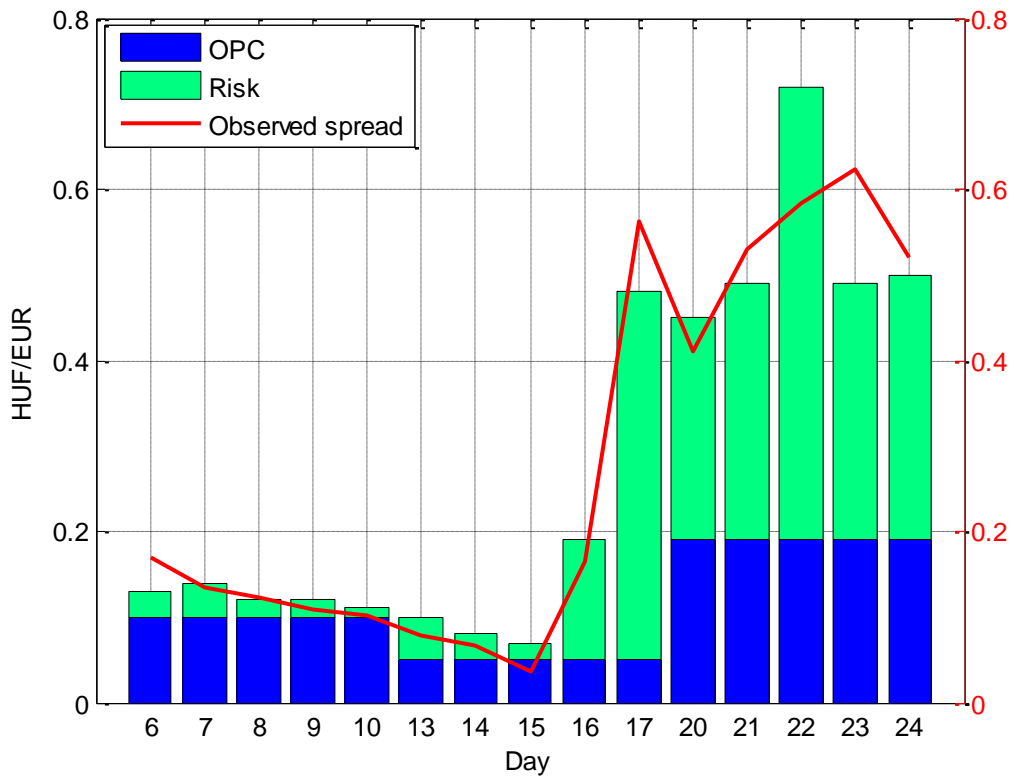


Figure 10: Spread components around the speculative attack (January 2003)

TABLES

	Whole sample	2003	2004
Number of quotes	437,420	193,447	243,973
Number of trades	72,622	31,978	40,644
Average trade size	1,304,398 EUR	1,339,827 EUR	1,276,523 EUR
Trades \leq 1 million €	80.38%	78.89%	81.55%
Trades >1 million € and <3 million €	13.79%	14.50%	13.23%
Trades ≥ 3 million €	5.83%	6.61%	5.22%
Average number of quotes per day	881.90	806.03	953.02
Average number of trades per day	146.42	133.24	158.77
Average daily trading volume (million €)	190.98	178.52	202.67

Table 1: Summary statistics

Chapter 4

Distribution of regression variables				
	25%	Median	75%	Mean
Quoted Spread (time weighted average)	0.15	0.21	0.34	0.32
Quoted Spread (last observation)	0.13	0.20	0.35	0.34
Volume Traded (million EUR)	2	9	20	16
Expected Volume Traded (million EUR)	6.25	12	15	10.19
Mid-Quote (time weighted; HUF/ EUR)	246.13	251.14	258.11	252.59
Volatility	2.24%	3.83%	6.11%	5.25%
Intra-Trade Time (minutes)	3	6.67	30	18.80
Mean of regression variables over time				
	2003 Jan-Jun	2003 Jul-Dec	2004 Jan-Jun	2004 Jul-Dec
Quoted Spread (time weighted average)	0.32	0.39	0.35	0.25
Quoted Spread (last observation)	0.32	0.39	0.39	0.25
Volume Traded (million EUR)	15.96	13.86	16.08	18.04
Expected Volume Traded (million EUR)	7.58	9.08	11.88	12.08
Mid-Quote (time weighted; HUF/ EUR)	247.26	259.80	256.02	247.32
Volatility	5.21%	6.08%	5.85%	3.90%
Intra-Trade Time (minutes)	21.86	19.64	16.55	17.30

Table 2: Summary statistics of the variables used in the regression

Chapter 4

	Spread (time weight.)	Spread (latest)	Volume (expected)	Volume (unexpected)	Volatility	Time btwn. trades	Option
Spread (time weight.)	1.00	0.34	-0.35	-0.05	0.23	0.38	0.56
Spread (latest)	0.34	1.00	-0.13	-0.01	0.07	0.14	0.18
Volume (expected)	-0.35	-0.13	1.00	0.06	0.04	-0.67	-0.30
Volume (unexpected)	-0.05	-0.01	0.06	1.00	0.29	-0.26	-0.12
Volatility	0.23	0.07	0.04	0.29	1.00	-0.14	0.60
Time btwn. trades	0.38	0.14	-0.67	-0.26	-0.14	1.00	0.43
Option	0.56	0.18	-0.30	-0.12	0.60	0.43	1.00

Table 3: Correlation matrix

Chapter 4

Period	Statistic	Mean Quoted Spread	Order Proc. Comp.		Risk Comp.	R ²
			Constant	E[Vol. Traded]		
2003-2004	Coefficient	0.3246	0.2920	-0.0137	3.9302	34.69%
	(t-statistic)		(8.95)	(-10.97)	(7.07)	
	Mean			10.1868	0.0434	
	Abs. Size Comp.		0.1529		0.1705	
Rel. Size Comp.	47.09%		52.52%			
2003 Jan-Jun	Coefficient	0.3185	0.2473	-0.0178	5.1544	40.95%
	(t-statistic)		(4.88)	(-7.99)	(4.65)	
	Mean			7.5833	0.0400	
	Abs. Size Comp.		0.1123		0.2064	
Rel. Size Comp.	35.26%		64.80%			
2003 Jul-Dec	Coefficient	0.3899	0.4111	-0.0205	3.1225	30.85%
	(t-statistic)		(10.10)	(-8.38)	(6.38)	
	Mean			9.0833	0.0528	
	Abs. Size Comp.		0.2251		0.1648	
Rel. Size Comp.	57.74%		42.26%			
2004 Jan- Jun	Coefficient	0.3453	0.3021	-0.0134	4.1700	33.75%
	(t-statistic)		(3.81)	(-4.70)	(3.60)	
	Mean			11.8750	0.0486	
	Abs. Size Comp.		0.1428		0.2025	
Rel. Size Comp.	41.35%		58.65%			
2004 Jul-Dec	Coefficient	0.2470	0.3007	-0.0118	2.5738	35.17%
	(t-statistic)		(5.53)	(-5.75)	(2.38)	
	Mean			12.0833	0.0324	
	Abs. Size Comp.		0.1584		0.0833	
Rel. Size Comp.	64.11%		33.73%			

Table 4: Regression results and spread components.

The option value was calculated under the assumption that there is one liquidity provider - the patterns were updated each half year - all t-statistics are corrected for heteroskedasticity

Chapter 4

Statistic	Constant	E[Vol. Traded]	Intra-trade time	Volatility	R ²
Coefficient (t-statistic)	0.2085 (8.08)	-0.0106 (-9.97)	58.6324 (12.10)	2.1611 (7.44)	23.53%
Mean		10.1868	0.0019	0.0525	
Average share in average spread size	64.23%	-33.32%	34.32%	34.95%	

Table 5: Regression with ad hoc specification

The patterns were updated each half year - all t-statistics are corrected for heteroskedasticity

Timing	Statistic	Mean Quoted Spread	Order Proc. Comp.		Risk Comp.	R ²
			Constant	E[Vol. Traded]		
Peak	Coefficient	0.2305	0.2155	-0.0054	2.5428	37.93%
	(t-statistic)		(7.52)	(-5.52)	(4.02)	
	Mean			13.70	0.0343	
	Abs. Size Comp.		0.1416	0.0872		
Rel. Size Comp.	61.41%	37.84%				
Non-peak	Coefficient	0.5096	0.2257	-0.0110	5.2225	
	(t-statistic)		(0.16)	(-1.90)	(2.50)	
	Mean			3.17	0.0616	
	Abs. Size Comp.		0.1909	0.3217		
Rel. Size Comp.	37.46%	63.13%				

Table 6: Spread components during peak and non-peak times

The patterns were updated each half year - all t-statistics are corrected for heteroskedasticity

Chapter 4

Timing	Statistic	Mean Quoted Spread	Order Proc. Comp.		Risk Comp.	R ²
			Constant	E[Vol. Traded]		
Week before attack (6-10/01)	Coefficient	0.1272	0.1713	-0.0091	1.9581	48.98%
	(t-statistic)		(8.99)	(-6.26)	(1.74)	
	Mean			7.58	0.0129	
	Abs. Size Comp.		0.1020		0.0253	
	Rel. Size Comp.		80.15%		19.85%	
Week of attack (13-17/01)	Coefficient	0.1817	0.1018	-0.0071	4.5233	59.87%
	(t-statistic)		(1.93)	(-1.31)	(5.90)	
	Mean			7.58	0.0295	
	Abs. Size Comp.		0.0481		0.1336	
	Rel. Size Comp.		26.48%		73.52%	
Week after attack (20-24/01)	Coefficient	0.5338	0.4830	-0.0383	5.8272	54.35%
	(t-statistic)		(3.45)	(-3.78)	(4.69)	
	Mean			7.58	0.0585	
	Abs. Size Comp.		0.1929		0.3409	
	Rel. Size Comp.		36.13%		63.87%	

Table 7: Spread components around speculative attack

The patterns were updated each half year - all t-statistics are corrected for heteroskedasticity

LIST OF REFERENCES

- Amihud, Yakov, and Haim Mendelson, 1980, Dealership market: Market-making with inventory, *Journal of Financial Economics* 8, 31-53.
- Anand, Amber, and Kumar Venkataraman, 2013, Should exchanges impose market maker obligations?, Available at SSRN: <http://ssrn.com/abstract=2179259> or <http://dx.doi.org/10.2139/ssrn.2179259>.
- Bagehot, Walter, 1971, The only game in town, *Financial Analysts Journal* 27, 12-14.
- Bessembinder, Hendrik, 1994, Bid-ask spreads in the interbank foreign exchange markets, *Journal of Financial Economics* 35, 317-348.
- BIS, 2004, Triennial central bank survey: Foreign exchange and derivatives market activity in 2004, 49.
- BIS, 2010, Triennial central bank survey: Report on global foreign exchange market activity in 2010., 95.
- Bjønnes, Geir H., Carol Osler, and Dagfinn Rime, 2008, Asymmetric information in the interbank foreign exchange market, *Norges Bank Working Paper Series*.
- Bjønnes, Geir H., and Dagfinn Rime, 2005, Dealer behavior and trading systems in foreign exchange markets, *Journal of Financial Economics* 75, 571-605.
- Black, Fischer, and Myron Scholes, 1973, The pricing of options and corporate liabilities *Journal of Political Economy* 81, 637-659.
- Bloomfield, Robert, Maureen O'Hara, and Gideon Saar, 2005, The “make or take” decision in an electronic market: Evidence on the evolution of liquidity, *Journal of Financial Economics* 75, 165-199.
- Bollen, Nicolas P.B., and William G. Christie, 2009, Market microstructure of the pink sheets, *Journal of Banking & Finance* 33, 1326-1339.
- Bollen, Nicolas P.B., Tom Smith, and Robert E. Whaley, 2004, Modeling the bid/ ask spread: Measuring the inventory-holding premium, *Journal of Financial Economics* 72, 97-141.
- Bollerslev, Tim, and Michael Melvin, 1994, Bid-ask spreads and volatility in the foreign exchange market: An empirical analysis., *Journal of International Economics* 36, 355-372.
- Branch, Ben, and Walter Freed, 1977, Bid-ask spreads on amex and the big board, *Journal of Finance* 32, 159-163.
- Danielsson, Jon, and Richard Payne, 2011, Measuring and explaining liquidity on an electronic limit order book: Evidence from reuters d2000-2, *European Journal of Finance* 18, 799-821.
- Demsetz, Harold, 1968, The cost of transacting, *Quarterly Journal of Economics* 82, 33-53.
- Easley, David, and Maureen O'Hara, 1992, Time and the process of security price adjustment, *The Journal of Finance* 47, 577-605.
- Evans, Martin D.D., and Richard K. Lyons, 2002, Order flow and exchange rate dynamics, *Journal of Political Economy* 110, 170-180.
- Evans, Martin D.D., and Richard K. Lyons, 2006, Understanding order flow, *International Journal of Finance and Economics* 11, 3-23.
- Foucault, Thierry, Marco Pagano, and Ailsa Röell, 2013, Market liquidity: Theory, evidence and policy, (Oxford University Press, USA).
- Frömmel, Michael, Xing Han, and Frederick Van Gysegem, 2013, News, liquidity dynamics and intraday jumps: Evidence from the huf/ eur market, *Mimeo*.
- Frömmel, Michael, and Frederick Van Gysegem, 2012, Spread components in the hungarian forint- euro market, *Emerging Markets Finance and Trade* 48, 52-69.
- Garman, Mark, 1976, Market microstructure, *Journal of Financial Economics* 3, 257-275.

- Glosten, Lawrence R., and Paul R. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71-100.
- Harris, Lawrence E., 1994, Minimum price variations, discrete bid-ask spreads, and quotation sizes, *Review of Financial Studies* 7, 149-178.
- Ho, Thomas, and Hans R. Stoll, 1981, Optimal dealer pricing under transactions and return uncertainty, *Journal of Financial Economics* 9, 47-73.
- Huang, Roger D., and Ronald W. Masulis, 1999, Fx spreads and dealer competition across the 24-hour trading day, *The Review of Financial Studies* 12, 61-93.
- Huang, Ruihong, and Hans R. Stoll, 1997, The components of the bid-ask spread: A general approach, *The Review of Financial Studies* 10, 995-1034.
- King, Michael R., Carol Osler, and Dagfinn Rime, 2011, Foreign exchange market structure, players and evolution, *Norges Bank Working Paper Series*.
- King, Michael, Lucio Sarno, and Elvira Sojli, 2010, Timing exchange rates using order flow: The case of the loonie, *Journal of Banking and Finance* 34, 2917-2928.
- Lyons, Richard K., 1995, Tests of microstructural hypotheses in the foreign exchange market, *Journal of Financial Economics* 39, 321-351.
- McGroarty, Frank, Owain ap Gwilym, and Stephen Thomas, 2006, Microstructure effects, bid-ask spreads and volatility in the foreign exchange market pre and post-emu, *Global Finance Journal* 17, 23-49.
- McGroarty, Frank, Owain ap Gwilym, and Stephen Thomas, 2009, The role of private information in return volatility, bid-ask spreads and price levels in the foreign exchange market, *Journal of International Financial Markets, Institutions & Money* 19, 387-401.
- Menkhoff, Lukas, and Maik Schmeling, 2010, Whose trades convey information? Evidence from a cross-section of traders, *Journal of Financial Markets* 13, 101-128.
- Merton, Robert C., 1973, Theory of rational option pricing, *Bell Journal of Economics and Management Science* 4, 141-183.
- Moore, Michael J., and Richard Payne, 2011, On the sources of private information in fx markets, *Journal of Banking & Finance* 35, 1250-1262.
- Osler, Carol, Alexander Mende, and Lukas Menkhoff, 2011, Price discovery in currency markets, *Journal of International Money and Finance* 30, 1696-1718.
- Phylaktis, Kate, and Long Chen, 2010, Asymmetric information, price discovery and macroeconomic announcements in fx market: Do top trading banks know more?, *International Journal of Finance & Economics* 15, 228-246.
- Stoll, Hans R., 1978, The pricing of security dealer services: An empirical study of nasdaq stocks, *Journal of Finance* 33, 1153-1172.
- Stoll, Hans R., 1978, The supply of dealer services in securities markets, *Journal of Finance* 33, 1133-1151.
- Tinic, Seha, 1972, The economics of liquidity services, *Quarterly Journal of Economics* 86, 79-83.
- Tinic, Seha, and Richard West, 1972, Competition and the pricing of dealer services in the over-the-counter market, *Journal of Financial and Quantitative Analysis* 8, 1707-1727.
- Tinic, Seha, and Richard West, 1974, Marketability of common stocks in Canada and the USA: A comparison of agent versus dealer denominated markets, *Journal of Finance* 29, 729-746.

Technical Note

The Reconstruction of the HUF/ EUR Limit Order Book using Book Data

In order to answer the research questions in this thesis, data from the limit order book at the intraday level was useful, and in many cases indispensable. Our dataset consists of all quotes, i.e., limit and market orders, on the HUF/EUR interbank market that have been placed during the years 2003 and 2004 via the Reuters D3000 broking system. We observe the price, the quantity in euro that was offered or asked, whether it was a market or a limit order and the exact time when the order was placed and when it disappeared. We observe whether the order was withdrawn or whether it was executed, i.e., matched with another limit or market order. Using this information we reconstruct the limit order book at the intraday level.

The raw tick-by-tick data we have consists for the two years together of 437421 rows of 28 columns containing numerical data and 3 columns containing strings. A substantial part of the information is double (see Appendix). We start from an empty limit order and trade book. Each time the book changes, we observe this change. From the raw data we can extract all incoming market and limit orders for the book , with for each order the time of entering, the time of removal or cancelation, the type of order¹, the quantity inserted, the quantity traded and the reason of removal.² The timestamp comes with 10 ms (0.01 sec.) precision. The orders are sorted on the time of entering. It is this information that forms the input for the limit order book reconstruction.

A new limit or market order and the cancelation of an existing limit order are events that lead to such a change. For the first type of events, the submission of limit orders or market orders, the event time will be the time of entering plus a latency factor.^{3,4} All activated limit orders are added to the relevant side of the book.⁵ The first and last state of the book in which each order can be found back is indexed. If the order is a market order or a marketable limit

¹ The types are: limit buy, limit sell, market buy or market sell order.

² These reasons are: „EntryCancelled“, „EntryHeld“, „EntryHit“, „EntryRemoved“, „EntryTaken“, „N/A“ and „UnsolicitedCancel“.

³ Except if the time of removal for this order was not reported. If this was the case the order was neglected. This was the case for 5579 out of 437421 orders.

⁴ This latency factor accounts for the small delay in the registration at the trading platform, cf. infra

⁵ Activated orders are the orders which have been entered before the event time, and which have not left the book at the event time. Activated orders should not be confused with active orders (i.e. orders which initiate a trade).

order it is verified with which activated order(s) the current order was matched.^{6,7} The orders that can be filled completely among these activated orders, which can obviously only be found at the other side of the book, leave the book. They are identified by comparing their time of removal with the time at which the market or marketable order entered the book. However, it can also be that market or marketable orders fill activated orders only partly.⁸ Because the order was only partly filled, it did not leave the book. In this case we adapt the liquidity of the activated order to the actual available liquidity for future orders. We identify these cases by checking whether the sum of the available volume(s) from the activated orders that leave the relevant side of the book at the time the market or marketable order was entered is smaller than the traded volume of the market or marketable order. If this is the case, the remaining volume of the market or marketable order is subtracted from the activated order that has the same quote.

Some marketable limit orders might not have been filled immediately: their quantity is bigger than the quantity of the activated order(s) with which it could be matched. In this case, the marketable limit order will stay in the book until new orders enter the book (or until the order is canceled). For all limit orders added to the book it is verified whether activated limit orders leave the other side of the book exactly when the limit order was entered. In contrast to the cases above, here the quantity of the freshly entered (and not the previously activated) limit order should be adapted: the quantity that was traded immediately is subtracted from the order size.

The limit book updates outlined above do all take place when certain orders enter the book. A third type of events that lead to limit order book updates are cancelations of existing limit orders in the book. For this reason it is verified whether after each order, one of the orders (or whether several ones) leave the book before the next order is submitted to the trading platform.⁹ Each time this happens, a new event is identified and added to the time series of limit order book states. The event time will here be the removal time of the order.¹⁰ Again, to obtain the new order book state the post-event orders are sorted according to price and time priority.

⁶ A marketable limit order is a limit order that can be immediately executed, because its price or equal to or better than the best quote from the opposite side of the book.

⁷ First we only treat marketable limit orders which are immediately completely filled.

⁸ A combination is also possible, i.e. the market or marketable order is partly matched with an activated order that was completely filled and partly with an activated order that was not completely filled.

⁹ Except if the order leaves the book in the last 800 ms. before the next order is entered. If this is the case, there is no separate event added for this event as delay in reporting could be responsible for the timegap.

¹⁰ Here no latency factor is added, as delay in the registration process is irrelevant for this type of updates

The output of the limit order book reconstruction process is a series of observations in event-time (every time the order book is updated, a new event is initiated), with for each event a timestamp at 10 ms. precision and all orders at the bid and ask side (with their respective quotes, quantities, record numbers, entering and removal times). For very short periods, zero or negative spreads can be observed. Their presence can be explained by the absence of clearing agreements between certain banks (in this case, the two banks who have posted the best orders at the respective sides of the book do not have such an agreement). As other banks, which do have clearing agreements with the issuers of the best orders from both sides, can take advantage of this situation, this zero or negative spreads are short-lived.

The output of the limit order book reconstruction process is a series of observations in event-time (every time the order book is updated, a new event is initiated), with for each event a timestamp at 10 ms. precision and all orders at the bid and ask side (with their respective quotes, quantities, record numbers, entering and removal times). For very short periods zero or negative spreads can be observed. Their presence can be explained by the absence of clearing agreements between certain banks (in this case, the two banks who have posted the best orders at the respective sides of the book do not have such an agreement). As other banks, which do have clearing agreements with the issuers of the best orders from both sides, can take advantage of this situation, these zero or negative spreads are short-lived. Timeseries are made by looking at the intervals needed. The information from the book is merged according to certain rules (e.g. values corresponding to the first state, last state, lowest and highest value, volume and time-weighted value,...). Legally recognized holidays in Hungary are left out.¹¹ Weekend days as well.

To conclude, we present an example of the level of detail the reconstructed book offers (See Figure 1). The dynamics between orders and midquote can now be observed in detail. This figure contains all euro buy orders (green) and all euro sell orders (red) on Feb. 13, 2003 from 15:45 till 16:15. Now we can observe the dynamics after a news announcement. At 15:57, Fitch affirms the Hungarian A long term foreign currency rating with a stable outlook. Immediately after this announcement there is a lot of volatility in the market because euro buy orders are added to the book, and euro sell orders are canceled or executed. During this process the midquote jumps up and down, and by 16:13 the quote seems to evolve to a new exchange rate level. This microscopic data was very important to answer our research

¹¹ For 2003 these were: 1/01, 15/03, 21/04, 1/05, 9/06, 20/08, 23/10, 1/11, 25/12 and 26/12. For 2004 these were: 1/01, 15/03, 12/04, 1/05, 31/05, 20/08, 23/10, 1/11, 25/12 and 26/12.

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questions, and can now further be used to study a plethora of issues related to the interaction on financial markets.

FIGURES

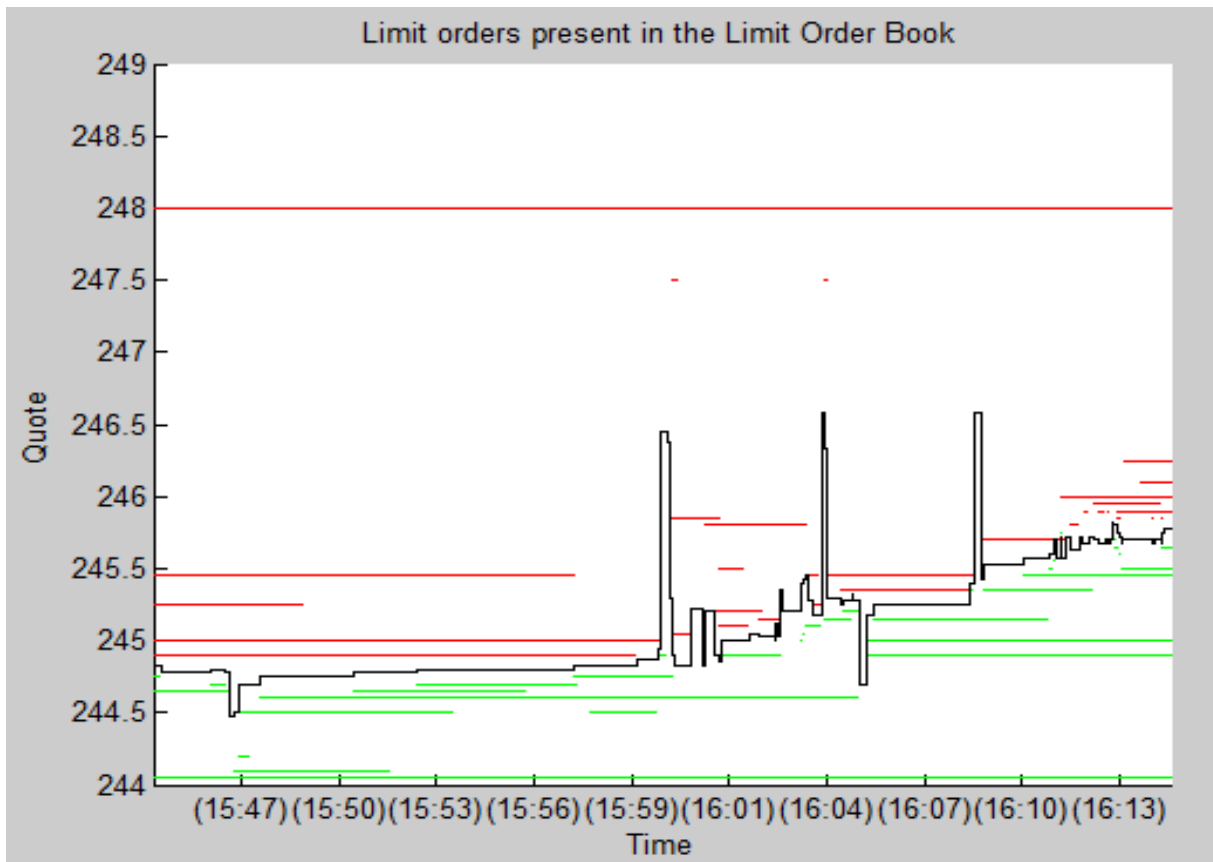


Figure 1: Detail of the reconstructed book (Feb. 13, 2003 from 15:45 till 16:15)

APPENDIX: ORIGINAL DATA

The raw data was consisting of 28 columns. Below the original description, explanation and type of data are summarized.

Col. 1: “Nap seged”; Numerical variable; Day in the month (1-31)

Col. 2: “Dátum”; Numerical variable; Datum in DD/MM/YYYY format

Col. 3: “Nap”; Numerical variable; Day in the month (1-31)

Col. 4: “Hónap”; Numerical variable; Month (1-12)

Col. 5: “Év”; Numerical variable; Year (2003-2004)

Col. 6: “Hét Napja”; Numerical variable; Day of the week (1-7)

Col. 7: “Day_entered2”; Numerical variable; Datum in DD/MM/YYYY format

Col. 8: “TIMEENTERED2”; String; Time at which the order was entered (GMT) in DD/MM/YYYY HH:MM:SS.MMM format (precise up to 0.01 sec.)

Col. 9: “Hour_ent”; Numerical variable; Hour at which the order was entered (GMT +1)

Col. 10: “Beadás perce”; Numerical variable; Minute of the day (GMT +1) during which the order was entered (1-1440)

Col. 11: “Kikerülés perce”; Numerical variable; Minute of the day (GMT +1) during which the order was removed (1-1440)

Col. 12: “TIMEREMOVED_2”; String; Time at which the order was removed (GMT) in DD/MM/YYYY HH:MM:SS.MMM format (precise up to 0.01 sec.)

Col. 12: “Hour_rem”; Numerical variable; Hour at which the order was removed (GMT +1)

Col. 13: “Enter-remove különbség (second)”; Numerical variable; Seconds between time of entering and time of removal (precise up to 0.01 sec.)

Col. 14: “TIMEENTERED”; String; Time at which the order was entered (GMT) in DD/MM/YYYY HH:MM:SS.MMM format (precise up to 0.01 sec.)

Col. 15: “Day_entered2”: Numerical variable; Datum in DD/MM/YYYY format

Col. 16: “Hour_enter1”: Numerical variable; Hour at which the order was entered (GMT) (1-12)

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Col.17: "Hour_enter2": Numerical variable; Contains 12 if the time in the previous column is p.m. and 0 if it was a.m. (0 or 12)

Col. 18: "Hour_enter": Numerical variable; Hour at which the order was entered (GMT) (1-24)

Col. 13: "Hour_enter_fin"; Numerical variable; Hour at which the order was entered (GMT) (1-24)

Col. 14: "Minute_enter_1"; Numerical variable; Minute, second and millisecond at which the order was entered (:MM:SS.MMM)

Col. 15: "Minute_enter_1"; Numerical variable; Minute, second and millisecond at which the order was entered (:MM:SS.MMM or :M:SS.MMM if minute is smaller than 10)

Col. 16: "Minute_enter_1"; Numerical variable; Minute, second and millisecond at which the order was entered (:MM:SS.MMM or :M:S.MMM if minute and/or second is smaller than 10)

Col. 17: "QUOTE"; Numerical variable; Quote of the order or price at which the market order was executed (up to 0.01 HUF/EUR)

Col. 16: "QUANTITYENTERED"; Numerical variable

Col. 17: "QUANTITYTRADED"; Numerical variable

Col. 18: "ENTRYTYPE"; Numerical variable

Col. 19: "MSGREMOVED"; String

Col. 20: "Hour_removed_fin"; Numerical variable

Col. 21: "Minute_removed"; Numerical variable

Col. 22: "Time_ent"; Numerical variable

Col. 23: "Minute_ent"; Numerical variable

Col. 24: "Second_ent"; Numerical variable

Col. 25: "Time (second) entered"; Numerical variable

Col. 26: "Minute_rem"; Numerical variable

Col. 27: "Second_rem"; Numerical variable

Col. 28: "Time (second) removed": Numerical variable

