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Essays on the FX Market Microstructure

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To my parents and Sofie

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Kevin Lampaert
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Nederlandstalige samenvatting

Dit doctoraal proefschrift is een collectie van vier essays die bijdragen tot een specifiek veld in “finance” genaamd “market microstructure”. Dit studieveld onderzoekt aspecten omtrent marktstructuren, -efficiëntie, liquiditeit en de dynamiek waarbij nieuwe informatie via reacties van verschillende marktparticipanten in de prijs wordt verdisconteerd. Het wijkt af van de basisstelling van volledig perfecte en efficiënte markten en start van het idee van non-frictieloze markten. Het onderzoeksveld analyseert de verschillende oorzaken die kunnen leiden tot tijdelijke divergenties van de werkelijke fundamentele prijs, aldus is de studie van de “market microstructure” relevant zowel in een academische als in een pure trading gerelateerde omgeving.

Het eerste hoofdstuk onderzoekt de impact van data frequentie op de “intraday” winstgevendheid van meer dan 8000 “technical trading rules” gebruikmakend van een ongeëxploreerde en unieke intraday dataset voor de Russische Roebel-US Dollar wisselkoersmarkt. De resultaten tonen aan dat winsten voortgebracht door deze technische handelsregels vaker voorkomen op een hoge trading frequentie. Evenwel verdwijnt de winstgevendheid na correctie voor echte gerealiseerde transactiekosten. Desondanks vinden we dat “technical trading rules” die toegepast worden op een voldoende hoge trading frequentie superieure rendementen kunnen opleveren in periodes waarbij een centrale bank een stabiliserend wisselkoersbeleid voert.

Het tweede hoofdstuk onderzoekt de mogelijke drijvers van “intraday momentum”, welke gedefinieerd is als een significante positieve relatie tussen het eerste en het laatste halfuur rendement. Op basis van dezelfde wisselkoersdataset voor de periode 2005 tot 2014, analyseren we de mogelijke drijvers van dit effect. Onze resultaten suggereren dat “intraday momentum” in de Roebelmarkt veroorzaakt wordt door risicoaversie t.o.v. het aanhouden van posities door liquiditeitsverschaffers doorheen de nacht. Bijkomend staven onze resultaten voorgaande studies die claimen dat marktconcentratie als gevolg van handelsuren belangrijk zijn voor “intraday momentum”, alsook dat dit effect sterker is tijdens crisissen.

In het derde hoofdstuk analyseren we de verschillende componenten van de “bid-ask spread” aan de hand van een decompositie model ontworpen voor ordergedreven markten. Ons onderzoek toont aan dat bijna de helft van de “bid-ask spread” toe te schrijven is aan adverse selectie waarvan het relatief belang daalt over de tijd. Dit suggereert dat zowel “market coverage” gestegen is als dat informatieassymetrieën gedaald zijn. Tot slot vinden we dat tijdens periodes van financiële stress, zoals onder meer tijdens de Russische crisis van 2014, marktparticipanten een substantieel hogere bescherming tegen adverse selectie eisen.

In het vierde hoofdstuk onderzoeken we de prestatie van verschillende trade classificatie regels. Onze resultaten suggereren dat bepaalde nieuwe transactie gebaseerde classificatie regels een substantiële verbetering t.o.v. het standaard Lee en Ready classificatie algoritme voortbrengen. Deze verbetering is het gevolg van een hogere classificatiekracht bij transacties die binnenin de quotes plaatsvinden. Ook de bulk volume classificatieregel presteert adequaat doch slechter dan de traditionele "tick-by-tick" classificatieregels.

English summary

This PhD dissertation is a collection of four essays that contribute to a particular field in finance namely market microstructure. The study of market microstructure deals with the design and functioning of financial markets, market efficiency, liquidity and the dynamics by which new information is discounted into prices through various market participants. It differs from the basic paradigm of fully perfect and efficient markets and starts from the idea of non-frictionless markets. Hence, the field investigates various aspects like informed trading and liquidity which are among the factors that cause asset prices to converge or temporarily diverge from their true fundamental price.

The first chapter examines the use and profitability of technical trading rules on a high frequency basis by using an extensive and unexplored sample of intraday data for the Russian Ruble-US Dollar foreign exchange market. The results indicate that technical trading profits seem much more present on a higher frequency basis. The adjustment for real, rather than estimated transaction costs wipes away most of the profits. However, we do find evidence that technical trading rules applied at a sufficiently high frequency generate superior returns when the central bank conducts a stabilizing exchange rate policy.

The second chapter investigates the likely drivers of 'intraday momentum', which is defined as a significantly positive relationship between the first half-hour and the last half-hour return. Using the same data set for the period between 2005 and 2014, we analyze the likely drivers of this effect. Our results suggest that intraday momentum in the Ruble market is induced by risk aversion to overnight holdings among liquidity providers. In addition, our results complement earlier findings that suggest that market concentration due to trading hours matters for intraday momentum and that the effect is more pronounced during crises.

The third chapter applies a spread decomposition model to analyze the bid-ask spread components for a novel foreign exchange market data set. We find that almost half of the spread is attributable to adverse selection which relative importance decreases over time. This is indicative of lower information asymmetries and higher market coverage over the period. During periods of financial stress, a substantial increase in market participants' demand for protection against adverse selection is found during the Russian crisis of 2014.

In the fourth chapter, we assess the accuracy of various trade classification rules which is of relevance for trade classification in other high-frequency data sets where the trade indicator information is absent. Our results suggest that certain novel classifications rules offer substantial improvements over standard used Lee and Ready classification algorithm. This is due to higher classifying power for trades occurring inside quotes. The bulk volume classification rule performs reasonably well albeit worse than the traditional tick-by-tick rules.

Chapter 1

Does Frequency Matter for Intraday Technical Trading?[1]

Finance Research Letters August 2016, Vol. 18, 177-183

1.1 Introduction

The use of technical analysis, which uses past prices to guide trading decisions, is strongly contested by many academics (Malkiel, 1996) due to its head to head position with the efficient market hypothesis. Nevertheless, surveys show that technical analysis still is a popular technique in the financial industry, particularly in the foreign exchange market. In a seminal paper, Taylor and Allen (1992) found that 94% of foreign exchange dealers in London used some form of technical analysis over short horizons which is confirmed by subsequent research (Menkhoff, 1997; Lui and Mole, 1998; Oberlechner, 2001; Cheung and Chinn, 2001; Cheung et al., 2004; Gehrig and Menkhoff, 2006; Menkhoff and Taylor, 2007). The fact that technical analysis is most heavily used on the foreign exchange market, is surprising at first sight, since this market is dominated by professional traders. However, the market shows various characteristics making it prone for technical analysis. First, the share of short-term (inter-dealer) trading is significantly higher than in other financial markets (Lyons, 2001). Second, there is a plethora of competing fundamental models and this lack of a consensus model may be a

[1] This chapter is bassed on joint work with Michael Frömmel (Ghent University)

reason for the popularity of technical analysis on foreign exchange markets (Menkhoff and Taylor, 2007). Third, central bank interventions on the foreign exchange market may produce exploitable technical trading opportunities (Saacke, 2002). Fourth, the forthcoming profits from the use of technical trading rules and exchange rate fluctuations are self-reinforcing (Schulmeister, 2006).

The empirical literature highlights that technical trading rules are more profitable in emerging economies and on the foreign exchange market. Park and Irwin (2007) report almost 100 'modern' studies between 1988 and 2004 and find annual net profits of 10-30% for emerging markets and 5-10% for the foreign exchange market. The former could be attributed to lower market efficiency in emerging markets due to less intense competition, a lower number of market participants (Lo, 2004) and the lack of sufficient publicly available information (Bessembinder and Chan, 1995). More recently, Neely and Weller (2013) argue that trading rule returns in foreign exchange markets remain significant but shifted towards emerging markets. Also Chang et al. (2014) find evidence for the profitability of moving average trading rules for emerging stock markets. Another argument highlights that the practice could have had merit in any market but that its profitability decreased over time (Olson, 2004; Qi and Wu, 2006; Schulmeister, 2009) driven by a continuous increase in market efficiency or to environmental changes suggested by the adaptive market hypothesis (Lo, 2004).

Despite the reported use on short term technical trading (Menkhoff and Taylor, 2007), the majority of empirical research is based on daily or lower frequency data, whereas only 6 out of 92 reported modern studies used intraday data (Park and Irwin, 2007). Furthermore, none of these studies examine the effect of trading frequency on technical trading profitability. Hence, this paper contributes at least fourfold to the literature by performing an intraday study on the Russian Ruble-US Dollar currency market. First, we analyze the profitability and hence focus on an emerging economy's exchange rate, therefore combining the two most promising markets in terms of profitable technical analysis. Second, our data set covers a long time span of more than ten years and is tick-by-tick data, thus collected at the highest possible frequency. Therefore the data set allows us to (i) observe how the profitability evolved over time and (ii) to sample the data at any desired frequency. Third, in contrast to existing studies, we observe the best bid and ask prices which makes it possible to apply the real transaction costs at any point in time, even if these are time-varying. Fourth and finally, we apply the recently developed statistical test by Hansen (2005) for statistical inference that applies multiple testing corrections for data snooping (Harvey et al., 2016). In summary, our analysis does not provide evidence that simple technical trading rules consistently generate superior returns in a context where they are argued to flourish. However, we do find evidence that when the central bank conducts a policy focusing on exchange rate stabilization, technical trading rules can generate superior returns when applied at a sufficiently high frequency. This suggests that information captured by technical trading rules during interventions are short-lived and only valuable when applied accordingly.

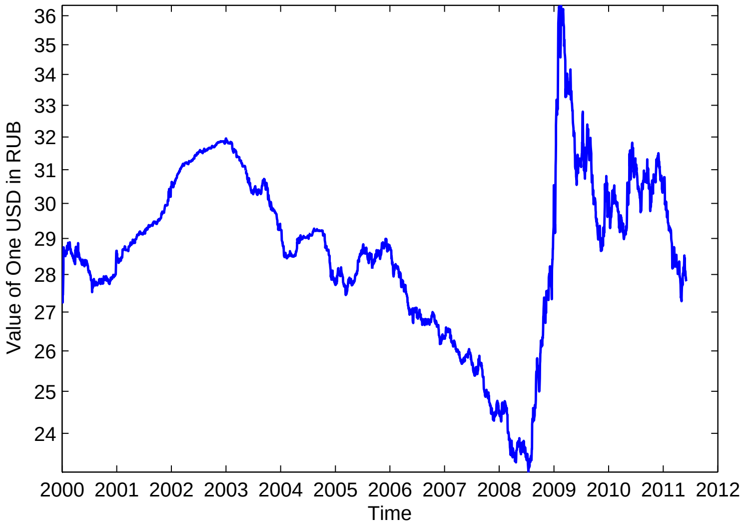
The remainder of the paper is organized as follows: section 1.2 describes the data. Section 1.3 reveals the implemented trading rules and statistical tests, section 1.4 provides and discusses the results and section 1.5 concludes.

1.2 Data

To assess the profitability of technical trading rules in a favorable environment, we collected a long time-span of tick-by-tick transaction data of the second largest BRICS-currency (Bank of International Settlement, 2013), namely the Russian Ruble versus the US Dollar. This data was gathered from the Moscow Interbank Currency Exchange (MICEX)[2] and spans the period from January 2000 till June 2011 as shown in figure 1.1. It contains information on date, time rounded to the nearest second, price, Dollar-volume and Ruble-volume for every transaction. We re-sample the tick data at a 10, 15, 30 and 60 minute frequency to analyze the trade-off between the short-lived value of information and higher transaction costs due to more trading.

[2]MICEX is the largest exchange in Russia and Eastern Europe. For foreign exchange, MICEX centralizes country-wide domestic RUB-USD trading on one single platform. This platform has been jointly developed with Reuters and provides similar trading features as for the Reuters or EBS (Electronic Brokerage Systems) trading platform.

Figure 1.1: Exchange rate RUB-USD



This figure displays the value of 1 USD in RUB plotted on the y-axis in log scale from 2000 till June 2011.

Additionally, the data contains information on the quoted spread and therefore we can observe real transaction costs on a tick-by-tick basis. While previous research rely on estimated transaction costs, we use real transaction costs instead. Since the spread determines the profitability of trading rules, we consider taking this time-varying character into account as essential. By using the observed spread we thus account for intraday patterns in the spread, changes in market liquidity and variations in the spread across exchange rate regimes. The upper panel in table 1.1 displays how the spread decreases over time while the lower panel displays spread summary statistics across exchange rate regimes. The spread is most tight for the dual currency band regime which lasted from 2005 till 2010. The pre-2005 managed floating regime has a spread that is almost twice as large as for the subsequent regimes which is attributable to lower liquidity during that sample period.

1.3 Trading rules and test design

1.3.1 Technical trading rules

In line with literature, we test for the presence of technical trading rule profitability based on two technical trading rules most popular among

Table 1.1: Summary Statistics Bid-Ask Spreads

Panel A: Yearly Spread Statistics

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Min	0.0025	0.0002	0.0025	0.0010	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Max	1.0100	0.9800	0.0900	0.0385	0.0250	0.0250	0.0250	0.0200	0.0340	0.0594	0.0350	0.0698
Mean	0.0255	0.0165	0.0114	0.0105	0.0113	0.0089	0.0069	0.0065	0.0068	0.0076	0.0072	0.0101
Median	0.0200	0.0200	0.0100	0.0100	0.0100	0.0090	0.0075	0.0060	0.0060	0.0070	0.0060	0.0100
Std	0.0227	0.0063	0.0043	0.0037	0.0037	0.0030	0.0030	0.0020	0.0029	0.0043	0.0041	0.0048
Perc (10%)	0.0140	0.0100	0.0100	0.0080	0.0080	0.0050	0.0020	0.0050	0.0050	0.0050	0.0044	0.0050
Perc (90%)	0.0400	0.0200	0.0160	0.0100	0.0170	0.0100	0.0100	0.0100	0.0100	0.0110	0.0100	0.0200

Panel B: Spread Statistics by Exchange Rate Regime

	Managed Floating	Dual Currency Band	Abandoned Formal Band
Min	0.0000	0.0001	0.0001
Max	1.0100	0.0594	0.0698
Mean	0.0171	0.0073	0.0090
Median	0.0150	0.0070	0.0100
Std	0.0147	0.0036	0.0048
Perc (10%)	0.0100	0.0045	0.0050
Perc (90%)	0.0220	0.0100	0.0160

This table provides summary statistics of the quoted spread for every year and for every exchange rate policy separately using tick-by-tick data.

Table 1.2: Overview Technical Trading Rules Parameterizations

Panel A: Moving Average Parameters											
Short term Lag	1	1	1	1	1	2	2	...	98	98	99
Long term Lag	2	3	4	...	100	3	4	...	99	100	100
Panel B: RSI Parameters											
Lower Bound	10	10	10	10	11	11	11	...	40	40	40
Upper Bound	90	90	90	90	89	89	89	...	60	60	60
Lag	2	3	...	100	2	...	100	...	2	...	100

This table presents the various trading rule parameterizations for the moving average (Panel A) and the RSI (Panel B) trading rule.

practitioners (Taylor and Allen, 1992) and most widely investigated in research (Park and Irwin, 2007). The first is one of the most popular in practice while at the same also one of the most vastly tested in academic research (Park and Irwin, 2007). In short, moving averages trading rules provide buy (sell) signal whenever the short moving average crosses the long moving average from below (above). The second applied popular trading rule in practice is an oscillator called RSI (Park and Irwin, 2007). The indicator values of the RSI swing between 0 and 100 and it is used to pinpoint overbought and oversold periods for a given security. The higher (lower) the current value of the RSI, the more it is overbought (oversold). In total we apply 4950 moving average and 3069 RSI trading rules as shown in table 1.2. We focus on these 2 trading rules since we expect that their long lasting popularity among practitioners may be the result of their sound performance.

1.3.2 Returns and transaction cost

In a next step, we calculate the trading rule returns as the logarithmic difference of two consecutive trading prices possibly adjusted with the current observed spread conditional on having a trading signal.

$$r_{k,t+1} = (\ln[P_{t+1} + hs_{t+1} \cdot S_{k,t+1}] - \ln[P_t + hs_t \cdot S_{k,t}]) \cdot D_{k,t} \qquad (1.1)$$

Where $r_{k,t}$ is the k^{th} return at time t+1, P_t, the mid-price at time t, hs the observed half spread, $S_{k,t}$ is the trading rule's (new) trading rule signal to buy or sell, and $D_{k,t}$ the k^{th} (existing) trading rule trading position at time t. This setting allows us to capture both the long run market evolution that contributes to lower spreads as well as temporary spread increases due to uncertainty or liquidity scarcity. Our research employs recent and time-varying spread data on a less liquid and more volatile exchange rate which stands in contrast to previous literature that estimates transaction costs in the nineties for major currencies and consecutively employs fixed transaction costs ranging from 0.03% to 0.08% (Bessembinder, 1994; Neely et al., 1997; Cheung and Chinn, 2001).

1.3.3 RC and SPA test

To accommodate for data snooping as a result of the various parameterizations (White, 2000; Harvey et al., 2016), we employ the "superior predictive ability" test of Hansen (2005) which tests whether the best trading rule has predictive power over a benchmark taking into account the full universe of tested trading rules. This test is based on the "reality check" test of White (2000). First, we calculate the performance statistic, $f_{k,t}$, as shown in equation 1.2, where b_t represents the benchmark return at time t, to assess the hypothesis that the best trading rule from the pool of various trading rules did not significantly outperform the benchmark: $H_0 : \max_{k=1 \to L} \{E(f_k)\} \leq 0$.

$$f_{k,t} = r_{k,t} - b_t \tag{1.2}$$

Hansen (2005) argues that the p-values from the "reality check" test of White (2000) are easily inflated by adding new poor models to the universe of the tested models. Therefore, he modifies the test statistic through studentization which enables comparison of the models in terms of units of standard deviation.

$$T^{SPA} = \max\left[\max_{k=1 \to L} \frac{\sqrt{N} \cdot \overline{f_k}}{\hat{\sigma}_k}, 0\right] \tag{1.3}$$

Additionally, he proposes to construct a data dependent null distribution to ensure that the influence from the poor alternative models is reduced. Hansen's (2005) solution therefore compares the average return over the benchmark to a certain threshold as shown in equation 1.5.

$$T_i^{SPA} = \max\left[\max_{k=1 \to L} \frac{\sqrt{N} \cdot \overline{Z}_{k,i}}{\hat{\sigma_k}}, 0\right] \tag{1.4}$$

With

$$\overline{Z}_{k,i} = \overline{f}_{k,i} - h_x\left(\overline{f}_k\right) \tag{1.5}$$

Where h_x equals either, h_c, h_l, or h_u representing the consistent, lower bound, and upper bound SPA p-values.

$$h_c\left(\overline{f}_k\right) = \begin{cases} \overline{f}_k \text{if} & \overline{f}_k \geq -\sqrt{\frac{\hat{\sigma}_k^2}{N} \cdot 2 \cdot \log\log N} \\ 0 \text{ if} & \overline{f}_k \leq -\sqrt{\frac{\hat{\sigma}_k^2}{N} \cdot 2 \cdot \log\log N} \end{cases} \tag{1.6}$$

$$h_l\left(\overline{f}_k\right) = \max\left(0, \overline{f}_k\right) \tag{1.7}$$

$$h_u\left(\overline{f}_k\right) = 0 \tag{1.8}$$

1.4 Results

We start our discussion with the results, as shown in table 1.3, based on a zero return benchmark without incorporating any transaction costs applying the SPA-test using a 1000 bootstraps and an average block length of 5[3]. From this table we can state that an increase in the trading frequency at which technical trading rules are performed has an advantageous effect on both the realized return and on its significance. In absence of transaction costs, we find that technical trading rules can exploit the market's incomplete and lagged information processing, especially in very short terms. Specifically, we find that at a 60-minute trading frequency, the consistent p-values are significant at a 10% level of significance for 5 out of 12 years. When we increase the trading frequency up to 30-minute intervals, the number of significant values increase to 8 at a 10% significance level from which 4 remain even significant at 1% significance level. At 15-minute intervals, the results become even stronger. In this case, technical trading rule returns have outperformed the zero return benchmark in 9 out of 12 years. At the highest frequency, a 10-minute trading frequency, again 9 out of 12 yearly results are significantly positive at a 10% significance level. Moreover, the previous result further improves in terms of a further reduction of the p-values. Next to these results, we also find that in tendency the number of transactions increases when the trading frequency is shortened. Therefore,

[3]This resembles to setting the parameter q equal to 0.2 in the stationary bootstrap of Politis and Romano (1994). Our results remain robust when using alternative average block lengths. Moreover, Sullivan et al. (1999) set q equal to 0.1 and perform 500 bootstraps, they report that their results are insensitive to the choice of the block length parameter.

Table 1.3: Overview results trading rules before transaction costs

	Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
60 minutes	Trading rule	RSI	MA	RSI	MA	RSI	RSI	RSI	RSI	MA	MA	RSI	RSI
	Parameters	18,70,30	75,76	2,63,37	17,29	2,61,39	2,65,35	2,70,30	2,62,38	2,73	3,5	41,65,35	7,84,16
	Transactions	7	9	267	9	509	591	497	491	37	379	25	17
	Return	10.23%	**6.03%**	**3.44%**	6.49%	**10.38%**	**19.83%**	9.32%	10.57%	24.48%	**36.58%**	23.69%	10.30%
	c	0.195	0.029	0.037	0.191	0.010	0.000	0.200	0.104	0.203	0.094	0.225	0.517
	l	0.169	0.022	0.029	0.146	0.010	0.000	0.162	0.080	0.147	0.075	0.191	0.454
	u	0.195	0.032	0.044	0.191	0.010	0.000	0.204	0.109	0.204	0.094	0.226	0.517
30 minutes	Trading rule	RSI	MA	RSI	MA	RSI	RSI	RSI	RSI	MA	MA	MA	MA
	Parameters	18,70,30	75,76	2,63,37	31,57	2,62,38	2,63,37	2,72,28	2,60,40	11,41	6,8	4,9	4,5
	Transactions	7	9	279	9	1015	1253	1023	1159	87	581	535	449
	Return	10.23%	**6.03%**	**3.69%**	**8.75%**	**19.04%**	**26.44%**	**14.25%**	**11.15%**	22.72%	**49.84%**	27.14%	13.30%
	c	0.188	0.030	0.022	0.022	0.000	0.000	0.006	0.083	0.348	0.003	0.160	0.250
	l	0.165	0.022	0.019	0.015	0.000	0.000	0.003	0.070	0.255	0.002	0.134	0.204
	u	0.188	0.031	0.023	0.022	0.000	0.000	0.006	0.085	0.349	0.003	0.163	0.250
15 minutes	Trading rule	RSI	RSI	RSI	MA	RSI	RSI	RSI	RSI	MA	MA	MA	MA
	Parameters	2,60,40	2,60,40	2,60,40	61,100	2,60,40	3,60,40	2,68,32	2,62,38	75,76	19,20	6,18	9,10
	Transactions	555	675	619	9	2163	2125	2399	2505	255	765	535	669
	Return	12.76%	**11.94%**	**6.97%**	**9.40%**	**32.16%**	**40.45%**	**20.12%**	**18.69%**	21.85%	**48.75%**	**30.02%**	12.93%
	c	0.167	0.000	0.000	0.020	0.000	0.000	0.000	0.000	0.459	0.005	0.090	0.379
	l	0.152	0.000	0.000	0.015	0.000	0.000	0.000	0.000	0.385	0.005	0.073	0.312
	u	0.168	0.000	0.000	0.021	0.000	0.000	0.000	0.000	0.460	0.005	0.091	0.379
10 minutes	Trading rule	RSI	RSI	RSI	MA	RSI	RSI	RSI	RSI	MA	MA	MA	MA
	Parameters	2,61,39	2,60,40	2,60,40	2,88	2,60,40	2,60,40	2,62,38	2,64,36	47,48	28,29	10,24	17,32
	Transactions	901	1037	1007	23	3319	4495	4265	3821	619	945	631	163
	Return	**20.58%**	**16.81%**	**11.60%**	**8.56%**	**58.53%**	**68.66%**	**37.94%**	**28.05%**	21.40%	**52.54%**	29.65%	14.71%
	c	0.000	0.000	0.000	0.058	0.000	0.000	0.000	0.000	0.558	0.004	0.110	0.197
	l	0.000	0.000	0.000	0.041	0.000	0.000	0.000	0.000	0.437	0.003	0.088	0.155
	u	0.000	0.000	0.000	0.062	0.000	0.000	0.000	0.000	0.560	0.004	0.111	0.202

This table provides based on a zero return benchmark without considering transaction costs the best trading rule, its corresponding parameters, number of transactions, returns and consistent, lower and upper p-values for the first traded contract over all considered trading frequencies. Trading rule returns that are significantly profitable at 10% or better based on the consistently p-value are displayed in bold. Results at a 5 minute frequency are in line with the reported results and available upon request.

the results could be biased and not representative for a real trading environment. To accommodate this problem, we apply transaction costs gathered from the observed bid-ask spread in our subsequent analysis. Overall we find that, incorporating the transaction costs deteriorate the best trading rule return to a great extent, as shown in table 1.4. As expected, imposing transactions costs based on the quoted spread largely reduces the trading rule returns. Specifically, we find at a 60-minute trading frequency that the consistent p-values are significant at a 10% level of significance for only 1 out of 12 years. When we increase the frequency up to 30-minute intervals, the number of significant values increase to 3 at 10% significance level, whereas on a 15-minute intervals, the results deteriorate. In this case, only 2 technical trading rules are found having significantly outperformed the zero return benchmark. At the 10-minute trading level, the results improve again with a total of 4 significant trading rule returns. We conclude that the lack of incorporating transaction costs in our previous analysis mostly explains the previous found increase in significant returns[4]. Overall, the results are far less outspoken compared the analysis above. Our findings based on the lower trading frequencies thus comply with Kuang et al. (2014) who show that the profitability of technical trading rule returns for various emerging FX markets are illusionary after taking into account transaction costs and data snooping biases. Nevertheless, in the case of the highest trading frequency, we find that on occasion – from 2003 till 2007– technical trading rules yield superior returns. This suggests that information captured by technical trading rules are short-lived and are only valuable when applied accordingly. Moreover, we find this result only during times when the Russian central bank imposed a managed floating regime and from 2005 onwards a dual-currency basket (Central Bank of the Russian Federation, 2013) aimed at reducing the volatility of the exchange rate. Taking these two findings together, our results comply with the literature suggesting that central bank interventions may create profit opportunities for technical trading rules (LeBaron, 1999; Saacke, 2002; Szakmary and Mathur, 1997), but only exploitable when trading at a very high pace.

[4]We find similar results when assessing based on a buy-and-hold benchmark both with and without adjustment for transaction costs.

Table 1.4: Overview results trading rules after transaction costs

	Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
60 minutes	Trading rule	MA	MA	MA	MA	MA	RSI	RSI	MA	MA	RSI	RSI	RSI
	Parameters	81,85	44,63	30,62	17,29	58,76	2,77,23	51,71,29	46,91	2,73	68,68,32	41,65,35	7,84,16
	Transactions	23	5	5	9	19	497	1	11	37	5	25	17
	Return	5.83%	5.69%	2.23%	6.21%	5.04%	10.01%	8.25%	10.06%	23.53%	33.82%	23.18%	9.63%
	c	0.891	0.065	0.420	0.239	0.386	0.296	0.336	0.151	0.262	0.172	0.275	0.603
	l	0.757	0.033	0.255	0.166	0.219	0.177	0.217	0.109	0.170	0.135	0.223	0.475
	u	0.936	0.152	0.673	0.241	0.662	0.389	0.415	0.184	0.265	0.174	0.290	0.617
30 minutes	Trading rule	MA	MA	MA	MA	RSI	RSI	RSI	RSI	MA	RSI	RSI	RSI
	Parameters	80,89	44,63	30,62	31,57	18,90,10	3,74,26	13,90,10	15,86,14	11,41	99,66,34	7,90,10	13,90,10
	Transactions	23	5	5	9	5	659	1	9	87	9	57	1
	Return	5.47%	5.69%	2.23%	8.47%	5.74%	14.56%	6.10%	10.38%	20.22%	37.15%	23.12%	7.12%
	c	0.928	0.064	0.425	0.042	0.477	0.027	0.865	0.135	0.513	0.131	0.380	0.969
	l	0.810	0.032	0.231	0.021	0.236	0.020	0.660	0.082	0.333	0.097	0.289	0.870
	u	0.966	0.146	0.702	0.044	0.816	0.070	0.946	0.196	0.547	0.134	0.411	0.983
15 minutes	Trading rule	RSI	MA	MA	MA	RSI	RSI	RSI	RSI	MA	MA	RSI	RSI
	Parameters	20,66,34	16,53	66,100	61,100	21,90,10	8,61,39	18,90,10	27,81,19	24,83	12,15	8,83,17	33,71,29
	Transactions	27	13	5	9	5	889	1	9	87	669	217	17
	Return	4.88%	4.64%	2.97%	9.12%	5.59%	20.65%	7.03%	10.32%	18.58%	32.39%	19.77%	9.26%
	c	0.982	0.399	0.292	0.034	0.583	0.001	0.771	0.160	0.681	0.290	0.657	0.825
	l	0.837	0.217	0.166	0.014	0.307	0.001	0.566	0.077	0.447	0.206	0.503	0.585
	u	0.992	0.766	0.701	0.065	0.961	0.006	0.937	0.335	0.745	0.322	0.780	0.908
10 minutes	Trading rule	RSI	MA	MA	RSI	RSI	RSI	RSI	RSI	MA	MA	RSI	MA
	Parameters	22,65,35	51,89	32,100	12,90,10	7,62,38	8,60,40	11,64,36	43,75,25	30,97	16,25	18,83,17	17,32
	Transactions	55	17	11	1	813	1447	753	9	123	505	45	163
	Return	5.49%	5.47%	3.26%	8.44%	9.87%	21.01%	10.67%	11.61%	18.18%	32.99%	20.59%	8.08%
	c	0.985	0.316	0.280	0.067	0.066	0.001	0.171	0.084	0.742	0.257	0.602	0.925
	l	0.829	0.143	0.137	0.033	0.029	0.001	0.109	0.050	0.498	0.178	0.410	0.691
	u	0.999	0.778	0.777	0.155	0.628	0.030	0.503	0.264	0.830	0.285	0.758	0.984

This table provides based on a zero return benchmark with considering transaction costs the best trading rule, its corresponding parameters, number of transactions, returns and consistent, lower and upper p-values for the first traded contract over all considered trading frequencies. Trading rule returns that are significantly profitable at 10% or better based on the consistently p-value are displayed in bold. Results at a 5 minute frequency are in line with the reported results and available upon request.

1.5 Conclusion

In our study we conclude that initially our results support the existence opportunities for technical trading strategies in the most favorable setting as suggested by literature (Park and Irwin, 2007). However by revisiting the impact of transaction cost on technical trading rule profits through the use of real, time-varying transaction costs, we find that trading rule returns deteriorate and do not significantly outperform the benchmark. Nevertheless, we do find some evidence that when the central bank conducted a policy of stabilizing the exchange rate, technical trading rules can generate superior returns when applied at a sufficiently high trading frequency. This suggests that information captured by technical trading rules are short-lived and are only valuable when applied accordingly.

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Chapter 2

Intraday Momentum in FX Markets: Disentangling Informed Trading from Liquidity Provision[1]

Journal of Financial Markets - *In Press*

2.1 Introduction

Market participants need time to interpret and react to new information. Consequently, the dissemination of news potentially leaves room for predictability over short horizons of time. Theoretically, participants' trades are likely to be informative of future returns, given that they can be expected to contain private information (Lyons, 1995).

A number of papers show that interdealer order flow in foreign exchange (FX) markets is indeed predictive of future returns. Payne (2003) shows that trades carry information and have a substantial permanent impact on prices. Similarly, Chordia et al. (2005) show that order flow predicts future returns over the very short horizon. More recently, Chordia et al. (2008) find that very short-term predictability is diminished

[1]This chapter is based on joint work with Gert Elaut (Ghent University) and Michael Frömmel (Ghent University).

when bid-ask spreads are narrower, indicating that liquidity enhances market efficiency through increased arbitrage activity. This finding suggests that liquidity also plays a role in the short-term predictability of returns.

Although most of the above studies focus on very short horizons, Gao et al. (2015) take a considerably longer perspective while staying in the field of intraday high-frequency data. In particular, these authors investigate the predictability of a security's first half-hour return on its last half-hour return and find that the former positively predicts the latter. This finding suggests that, in addition to predictability over very short periods of time, there also appears to be predictability over considerably longer periods of time during the trading day. To date, however, no studies have empirically tested the likely drivers of this 'intraday momentum'.

Our contribution to the literature on FX microstructure is twofold. First, by using a long sample of transaction-level FX market data at tick frequency, we construct high-frequency measures of the likely drivers of intraday momentum in the Ruble market. Using these measures, we analyze whether intraday momentum is stronger on days with more informed trading or when demand for liquidity is higher. These hypotheses capture the likely explanations of how market participants' behavior may generate the observed intraday momentum effect.

For the RUB-USD FX market, and contrary to the results of Gao et al. (2015) for the equity market, we do not find any evidence supporting the idea that intraday momentum is the result of strategic informed trading during the opening and closing of the trading session. This finding is consistent with the earlier finding that informed traders in the RUB-USD FX market mainly trade during the opening of the trading sessions in the Moscow Interbank Currency Exchange (MICEX) (Menkhoff and Schmeling, 2010). Instead, our results for the Ruble market indicate that opening half-hour returns positively predict closing half-hour returns on days when bid-ask spreads are high during the opening half-hour. We hypothesize that high spreads are consistent with higher levels of liquidity provision by some market participants following heavy trading early in the morning. Taken together, our results lend support to the argument that risk aversion to overnight holdings and a potential disposition effect among liquidity-providing market participants drive intraday momentum in the Ruble market.

Second, our findings also contribute to a better understanding of intraday momentum along several other dimensions. In particular, we corroborate the finding of Gao et al. (2015) that the trading hours of the non-major currency's domestic market matter for intraday momentum.

Although these authors observe a general lack of intraday momentum in major currencies vis-à-vis the US Dollar when considering US trading hours, they find some weak evidence of intraday momentum when they determine implicit trading hours, based on increases in volume in international equity index futures. Our results for the RUB-USD currency pair show that, by considering the *explicit* trading hours of the MICEX, significant levels of intraday momentum are present. Clearly, the explicit nature of the trading hours helps to identify the relevant periods over which intraday momentum occurs in this FX market. Finally, our results also support the earlier observation that intraday momentum is more pronounced during crisis periods.

The remainder of this paper is structured as follows. In Section 2.2, we provide an overview of the related literature and formulate the different mechanisms that may drive intraday momentum. In Section 2.3, we describe the data used for our empirical analysis. Section 2.4 outlines the concept of intraday momentum and presents the methodology used to measure the degree of informed trading and liquidity demand. Section 2.5 provides and discusses the results. We conclude in Section 2.6.

2.2 Motivation and Related Literature

Gao et al. (2015) suggest two potential mechanisms that may drive intraday momentum in financial markets. First, the intraday pattern can be the result of liquidity provision by some market participants (e.g., day traders, market makers, etc.). With price dissemination being the highest at the beginning of a trading session (Bloomfield et al., 2005) – market participants react to macroeconomic news released overnight before the start of the trading session – temporary imbalances may arise when market participants react similarly to news. Day traders and market makers may be motivated to take opposite positions to provide liquidity to the market. However, although these traders may quickly close out winning positions throughout the day, they may be more reluctant to rapidly close out losing positions. However, the prospect of having to hold positions overnight may convince traders and market makers to close out the positions nonetheless. Gao et al. (2015) point to a disposition effect among (day) traders (Odean, 1998; Locke and Mann, 2005) to motivate such asymmetric behavior. The risk management practices of financial institutions, however, may similarly force traders to close out positions before the end of the day. This behavior of (foreign exchange) dealers' offloading undesired inventory has been widely documented in the literature (Lyons, 1995; Bjønnes and Rime, 2005).

Second, intraday momentum is also theoretically consistent with the strategic behavior of informed traders. Theoretically, Kyle (1985) and Admati and Pfleiderer (1988) argue that informed traders will time their trades during high-volume periods to hide their information advantage and to limit the price impact. Doing so will force informed traders to trade in high-volume periods (see Bloomfield et al., 2005). Given the well-known U-shape in intraday trading volume, the implication is that they will trade at the beginning and near the end of the trading day. If informed traders indeed place their trades during periods of heavy trading and if their trading has a (permanent) price impact, then this may also drive the observed predictability in intraday returns.

Both explanations are closely related to the existing FX microstructure literature that investigates the predictability of returns in FX markets. Research indicates that fundamentals, proxied with macroeconomic variables, perform poorly in predicting future exchange rate movements (e.g., Evans and Lyons, 1999); however, this is not the case for order flow and liquidity. In particular, it is well founded that order flow predicts returns over the very short term. For example, Payne (2003) shows that market participants' trades carry information and have a substantial permanent impact on prices. Similarly, Chordia et al. (2005) show that order flow predicts future returns over the very short horizon.

Theoretically, the predictability of future returns based on order flow is consistent with strategic order splitting among informed traders. Given that information among market participants is heterogeneous, some participants are likely to participate in strategic trading to disguise their superior information. One way to lower the impact of their trades is through order splitting (Chakravarty, 2001), which results in correlated trades.

Love and Payne (2008) show that there is short-term predictability through order flow when public information is released, which suggests that the predictability is driven by information processing. Simultaneously, Evans and Lyons (2005) show that FX markets incorporate news only gradually, over the matter of a few days, rather than instantaneously. Similarly, Rime et al. (2010) confirm gradual learning and show that order flow is a strong predictor for daily returns. The above literature indicates that both transitory and permanent price impacts seem to be predictable from past order flow, at least over short horizons.

The recent literature has also started to consider that liquidity is an important explanatory variable in the price discovery process. Chordia et al. (2008) find that very short-term predictability is diminished when bid-ask spreads are narrower, indicating that liquidity enhances market efficiency through increased arbitrage activity. More recently, Boudt and Petitjean (2014) show that changes in order imbalances are informative of price discovery. This finding suggests that liquidity also plays a role in the short-term predictability of returns.

2.3 Data Description and Institutional Features

2.3.1 Data

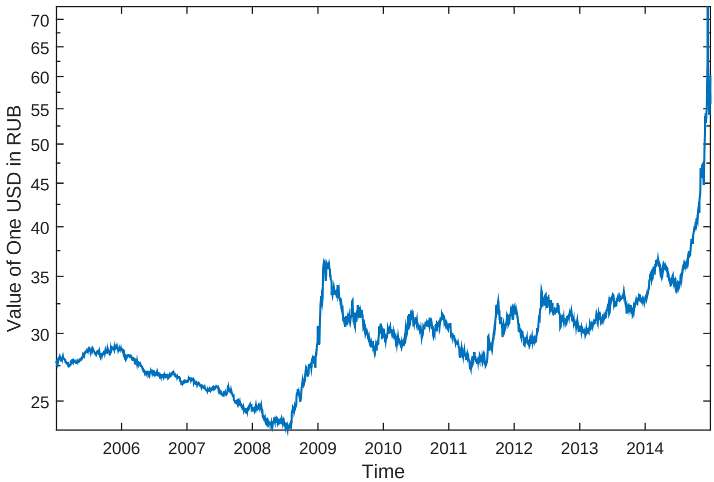
We use a particularly long-time span of intraday transaction-level data at tick frequency on the Russian Ruble-United States Dollar (RUB-USD). We obtain the data from the MICEX, the largest exchange in Russia and Eastern Europe. Spot trading in the RUB-USD currency pair equals 1.66% of total FX spot trading volume in 2013, meaning that the currency pair ranks as the 12th mostly heavily traded globally.

The period for which we are able to obtain data covers the period from January 12, 2005, to December 30, 2014. Although constrained to one particular currency pair, the data set offers several advantages. First, a long data span avoids a number of short sample problems that researchers often encounter in the microstructure literature, such as possible structural breaks or biases in the estimated parameters. Second, the sample period features both the Global Financial Crisis of 2007-2009 and the more recent Russian crisis of 2014, during which the Russian Ruble was the object of the crisis. Figure 2.1 illustrates the evolution of the RUB-USD exchange rate over the sample period.

Both the Global Financial Crisis and the Russian crisis are clearly discernible, with both instances leading to a meaningful depreciation in the value of the RUB versus the USD. The figure also suggests somewhat higher volatility post-2008 compared to the first couple of years of the sample period.

The MICEX trading platform was jointly developed with Reuters and has features similar to the platform of Reuters or Electronic Brokerage Systems (EBS). Participants can observe the price, the trading volume, and the bid- and ask prices with standing volumes. In contrast to most other FX markets, it is only possible to submit limit orders to the platform. However, market orders can be synthetically created by submitting marketable limit orders. The MICEX covers all domestic spot trading in Russia. Offshore trading in the RUB-USD is performed through and limited to non-deliverable forward contracts. To illustrate the fact that both platforms are very similar and that the MICEX is the main exchange for spot trading in RUB-USD worldwide, we note that trading on Thomson Reuters is transmitted to the MICEX during trading hours when the MICEX is open. We refer to Menkhoff and

Figure 2.1: Evolution United States Dollar - Russian Ruble (2005-2014)



This figure displays the value of 1 USD in RUB plotted on the y-axis in log scale from January 2005 till December 2014.

Schmeling (2010) for further details on Ruble trading on the MICEX.

The data set contains the following information for every trade executed on the MICEX; a time-of-day time stamp (to the millisecond), the price at which the order is executed, and the size of the trade. Simultaneously, we also have information on the best bid- and ask price at the time every order is executed. From the transaction-level data, we calculate half-hour (30 minutes) log returns for each trading day t as follows:

$$r_{j,t} = log\left(\frac{p_{j,t}}{p_{j-1,t}}\right) \tag{2.1}$$

where $r_{j,t}$ represents the half-hour return at day t for intraday interval j and $p_{j,t}$ represents the exchange rate at day t (the value of one US Dollar quoted in Russian Rubles) at the end of intraday interval j. The first half-hour return of each day is calculated based on the previous day's closing price. This way we also capture the overnight return component, which might drive the informed trading and liquidity demand we wish to analyze. At the same time, by using the previous day's closing price we avoid relying on the opening price. This is an important consideration, since the opening price is prone to pricing errors that may bias opening returns (see Amihud and Mendelson, 1987). Table 2.1 reports the summary statistics for the first and last half-hour returns used in this paper. We report statistics both for the full sample period and for the crisis periods separately.

We observe that opening half-hour returns are considerably more variable than closing half-hour returns, which reflects information processing at the start of the trading session. In addition, both return series are negatively skewed, suggesting that large negative returns are considerably more prevalent than large positive returns.

2.3.2 Institutional Features

The data set we consider has several features that we should bear in mind before we continue. First, and particular to the MICEX, the exchange has changed the opening and closing hour on several occasions over the sample period. In all instances, the change in trading hours led to an increase in the number of hours that the MICEX is open for trading. Table 2.2 provides an overview of the changes in trading hours.

The changes in the number of trading hours imply that the amount of time between the first half-hour return and the last half-hour return, the returns of interest, is not constant throughout the sample period. Because intraday momentum is expected to occur mainly during the start and the end of the trading day, however, we expect that the phenomenon is unaffected by the particular time of day with which the trading half-hours correspond.

Second, we note that foreign exchange markets are generally considered to be open virtually around the clock, with at least one major exchange trading the major currency pairs virtually at any point in time during the week. As such, the notion of first half-hour and last half-hour returns in the case of foreign exchange markets may seem inappropriate. Although this is true, trading intensifies considerably when a currency's domestic financial market commences trading. Furthermore, returns, spreads, and volatility are impacted by the market activity of various financial centers (Andersen and Bollerslev, 1997). Therefore, it can be argued that foreign exchange markets generally have implicit opening and closing trading hours. In the case of our data set, trading in the currency pair is organized during a fixed trading session, providing us with explicit opening and closing hours.

Nonetheless, to the extent that market participants trade outside the trading hours of the MICEX, this particular feature of the FX market may work against finding intraday momentum. Simultaneously, both explanations for intraday momentum crucially depend on liquidity considerations. Thus, if the observed intraday momentum described above is driven by the particular behavior of traders suggested by both explanations, then they will likely trade between the trading hours of the

Table 2.1: Summary Statistics RUB-USD Exchange Rate

	Panel A: Full Sample Period (2005-2014)		**Panel B: Financial Crises (2007-2009 & 2014)**	
	First Half-hour Returns	Last Half-hour Returns	First Half-hour Returns	Last Half-hour Returns
Mean	-0.001%	0.004%	0.004%	0.004%
Standard Deviation	0.589%	0.124%	0.798%	0.159%
Skewness	-1.842	-5.204	-2.278	-7.060
Kurtosis	56.896	138.337	45.945	132.897
Min	-8.932%	-2.943%	-8.932%	-2.943%
Max	6.265%	1.218%	6.265%	0.735%
# of Observations	2,342	2,342	922	922

This table reports summary statistics for RUB-USD exchange rate. We report statistics for both the first and the last half-hour return. Panel A contains the statistics for the full sample period 2005-2014, Panel B contains the statistics for the crisis periods (2007-2009 & 2014).

Table 2.2: Overview Trading Sessions on the MICEX Exchange for the RUB-USD

Period	Opening	Closing
01/01/2005 - 11/11/2008	10:00	14:00
12/11/2008 - 12/04/2013	10:00	15:00
13/04/2013 - 31/12/2014	10:00	17:00

Notes: trading hours in Moscow local time (GMT+3).

MICEX.

Finally, we should also briefly consider the particular institutional circumstances implied by FX markets. It is well known that trading on these markets is reserved to major banks and large institutional companies. This direct trading between major dealers covers the vast majority of foreign exchange traded volume and is often referred to as the first tier or wholesale tier. Our data set covers the trades executed on this wholesale tier market. Retail investors, mutual funds, and large non-financial corporations are, however, not directly active on this tier. Instead, these investors transact bilaterally with banks or brokers who provide quotes. Depending on the inventories of the banks and brokers with which these investors transact, these investors' orders may or may not be passed on to the wholesale tier. This particular market structure implies that retail investors will only indirectly impact the foreign exchange market. As such, it is ultimately the manner in which market makers pass the resulting inventory changes to the wholesale tier that matters. We can imagine that, if the liquidity needs of investors in the retail tier are large enough to materially impact the inventories of the market makers, then the effect will propagate to the trading on the wholesale tier. Despite this intricacy that follows from the two-tier structure of foreign exchange markets, we note that trading on the wholesale tier strongly outweighs trading on the retail tier. The forces driving intraday momentum can be at play between participants in the wholesale tier, and we directly observe (the price impact of) this trading.

From the above discussion, we can conclude that the particular structure of FX markets does not, a priori, rule out the possibility of intraday momentum in foreign exchange markets, although some features can be expected to work against observing an intraday momentum effect.

2.4 Methodology

To determine the existence of intraday momentum, we closely follow the approach used by Gao et al. (2015) and estimate predictive regressions. These authors note that the predictive regressions correspond to AR models. Although this is true, changes to the trading hours by the MICEX over the sample period imply that, in our case, the exact lag length of the AR model varies over time (see Section 2.3). We therefore express the predictive regression as follows:

$$r_{l,t} = \alpha + \beta r_{f,t} + \epsilon_t \tag{2.2}$$

where $r_{f,t}$ is the first half-hour return and $r_{l,t}$ is the last half-hour return. We also consider the predictive value of the penultimate return, which we denote as $r_{sl,t}$. The inclusion of this term allows us to control for any short-term persistence in the exchange rate during the day and to isolate the predictive value of the last half-hour return.

To investigate the relationship between informed trading and intraday momentum, we construct the Dynamic Probability of Informed Trading (DPIN) suggested by Chang et al. (2014). This measure builds on the empirical work of Avramov et al. (2006) and Campbell et al. (1992) and allows us to measure the degree of informed versus uniformed trading based on high-frequency transaction-level data. More specifically, this approach allows us to measure and track the presence of informed trades throughout the trading day on a high frequency. The fact that financial markets are becoming increasingly computer-driven – potentially making private information increasingly short-lived – makes measuring informed trading at the intraday increasingly important. The approach of Chang et al. (2014) allows us to avoid a degradation to lower frequencies of the PIN measure originally proposed by Easley et al. (1997).

Following Chang et al. (2014), we first perform a regression to isolate the unexpected half-hour return component (ϵ_t) from the return series while controlling for day-of-the-week effects (using the dummy variables denoted as D_j^{day}), time-of-day-effects (using the dummy variables denoted as D_j^{int}), and lagged half-hour returns (r_{t-k})[2]:

$$r_t = \alpha_0 + \sum_{i=1}^{4} \alpha_{1i} \cdot D_i^{day} + \sum_{j=1}^{J} \alpha_{2j} \cdot D_j^{int} + \sum_{k=1}^{12} \alpha_{3k} \cdot r_{t-k} + \epsilon_t \tag{2.3}$$

Autocorrelation patterns in unexpected returns (or a lack thereof) indicate the presence of uninformed (informed) trading. In particular,

[2] Where J equals the amount of intraday 30-minute intervals in the specific period.

Avramov et al. (2006) note that trades that take liquidity generate (future) price reversals. At the same time, sell trades in the presence of positive unexpected returns do not exhibit any autocorrelation and therefore indicate informed trading. Chang et al. (2014) argue that this can be extended to buy trades. The authors point out that buy trades in the presence of negative unexpected returns do not exhibit any autocorrelation, which again implies informed trading. Following (Chang et al., 2014) our measure of informed trading is calculated as follows:

$$DPIN_t = \frac{NB_t}{NT_t} \cdot (\epsilon_t < 0) + \frac{NS_t}{NT_t} \cdot (\epsilon_t > 0) \tag{2.4}$$

where NB_t, NS_t, and NT_t are the number of buy, sell, and total trades made during the half-hour interval, respectively, from t to $t-1$ and $(\epsilon_t < 0)$ and $(\epsilon_t > 0)$ are sign indicators that equal one when the unexpected return is smaller and larger than zero, respectively, and zero otherwise.

To analyze the alternative explanation, i.e., whether liquidity provision to some extent drives intraday momentum, we require a measure that identifies the trading days in which market participants can be expected to have provided liquidity to the market. For purposes of analysis, we focus on the tightness dimension of liquidity (Kyle, 1985). This is the main dimension of liquidity and is measured using the Equal-Weighted Quoted Spread (EWQS). This metric measures the average bid-ask spread over a given period of time. We hypothesize that, on days where the EWQS was higher during the first half-hour, more liquidity was demanded by market participants (e.g., as a consequence of economic news that was released overnight), meaning that some day traders or market makers are more likely to have provided the required liquidity.

2.5 Results

2.5.1 Intraday Momentum in RUB-USD

We start by running a set of predictive regressions in the spirit of Gao et al. (2015). In particular, we explore whether the first half-hour return, the penultimate half-hour return, and a combination of both independent variables are able to predict the last half-hour return. The results are reported in Table 2.3.

The results for the entire sample, reported in Panel A, indicate that there is no significant relationship between the last half-hour return and the first half-hour return. Although the coefficient has the expected sign,

Table 2.3: Predictability of Last Half-Hour Return

	Panel A: Full Sample			**Panel B: Crisis (2007-2009 & 2014)**			**Panel C: Excluding Crisis**		
Variables	r_l	r_l	r_l	r_l	r_l	r_l	r_l	r_l	r_l
r_f	0.0428		0.0412*	0.0698*		0.0656**	-0.0097		-0.0097
	(0.028)		(0.025)	(0.038)		(0.031)	(0.011)		(0.011)
r_{sl}		-0.1642	-0.1493		-0.2716	-0.2271		0.0020	0.0033
		(0.148)	(0.124)		(0.234)	(0.178)		(0.054)	(0.053)
Intercept	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,342	2,342	2,342	922	922	922	1,420	1,420	1,420
R^2 (%)	4.3	1.9	5.9	12.2	5.1	15.7	0.2	0.0	0.2

This table reports the results for the sample period January 12, 2005 to December 30, 2014 by regressing the closing half-hour return (r_l) on the first half-hour return (r_f) and the second last half-hour return (r_{sl}). Panel A contains the results for the full sample period whereas panel B reports the results for the crisis periods. Panel C contains the results for the non-crisis periods.

Newey and West (1987) robust standard errors in parenthesis. Significance at 1%, 5%, and 10% level indicated by ***, **, and *, respectively.

it is not significant at conventional levels, with a p-value of 0.12. The results for the penultimate half-hour return are similar, although the relationship appears to be even weaker. When we include both intraday returns in the predictive regression, however, the coefficient on the first half-hour return becomes significant at conventional levels, albeit only at the 10% level[3]. These results, although suggestive, are somewhat thin.

Second, we examine whether the relationship differs in periods of financial stress. We classify the Global Financial Crisis of 2007-2009 and the Russian crisis of 2014 as periods of financial distress. The results, reported in Panel B and Panel C of Table 2.3, indicate that intraday momentum is considerably more pronounced during periods of financial stress. During non-crisis periods, however, the relationship does not appear significant. This finding is consistent with the findings of Gao et al. (2015), who find that intraday momentum is more pronounced during the 2007-2009 Global Financial Crisis.

Third, to test the predictive ability of intraday momentum out-of-sample (OOS), we also perform out-of-sample forecasts. In particular, we run the above predictive regression with expanding windows, adding one day at a time. Using the estimated coefficients of the predictive regression (denoted using hats) and the value of the predictive variable at time s, we predict the return at time $s+1$:

$$\hat{r}_{l,s+1} = \hat{\alpha} + \hat{\beta} r_{f,s} \tag{2.5}$$

We perform these estimations for $s = s_0, ..., t-1$, thus generating a time series of out-of-sample return forecasts. s_0 is the initial sample size used to estimate the model (in our application, 4 years). We then estimate the OOS R^2 to measure out-of-sample predictability:

$$OOS\, R^2 = 1 - \frac{\frac{1}{T-s_0}\sum_{s=s_0}^{T-1}\left(r_{l,s+1} - \hat{r}_{l,s}\right)^2}{\frac{1}{T-s_0}\sum_{s=s_0}^{T-1}\left(r_{l,s+1} - \bar{r}_{l,s}\right)^2}, \tag{2.6}$$

where $\bar{r}_{l,s}$ is the historical mean of the last half-hour return, calculated from the expanding window of last half-hour returns. To test the significance of the OOS R^2, we employ the F-statistic of McCracken (2007). In Table 2.4, we report the results for the OOS R^2.

Similarly to Gao et al. (2015), we obtain a significant OOS R^2 of approximately 1.6%. This level of OOS R^2 is very substantial compared

[3]One potential reason could be microstructural issues such as bid-ask bounces, which cause intraday returns to exhibit mean-reverting behavior over short intervals.

Table 2.4: Out-Of-Sample Predictability

	OOS R^2	MSE-F
r_f	1.609%	21.948***
r_{sl}	-0.086%	-1.151
r_f and r_{sl}	1.640%	22.371***

This table examines the out-of-sample predictability of the last half-hour by the first half hour return and the second-to-last half-hour return, using a set of recursive regressions. The initial sample period (s_0) is 4 years (2005-2008).
Asterisks indicate statistical significance of the OOS R^2 using the MSE-F test

$$MSE - F = (T - s_0)\left(\frac{MSE_m - MSE_p}{MSE_p}\right).$$

Asymptotic critical values for the MSE test provided by McCracken (2007) used to test significance.
Statistical significance at the 10%, 5%, and 1% level given by *, **, and ***, respectively.

to other works (e.g., Campbell and Thompson, 2008; Ferreira and Santa-Clara, 2011). Simultaneously, the penultimate return does not seem to have any out-of-sample predictive power.

A second method of testing the economic significance of the results is by analyzing the returns accruing to a strategy that uses signals based on the first half-hour return. Here, we also closely follow Gao et al. (2015). We take a long or short position at the beginning of the final half-hour period, depending on the return of the opening half-hour, and close out the position at the end of the trading day. We benchmark the performance of this strategy to a constant long strategy that always goes long at the beginning of every final half-hour and that closes out the position at the end of every trading day[4].

The results in Table 2.5 indicate that, at least for the full sample period, the market timing strategy does not outperform the always long strategy. Interestingly, however, the returns to the intraday momentum strategy are positively skewed. This finding is in contrast to the always long series which, similar to the original first and last half-hour returns, is strongly negatively skewed. The disappointing performance of the strategy over the full sample matches the earlier observation that

[4]We note that the returns to both strategies are comparable because both strategies have identical turnover and thus incur similar levels of transactions costs.

Table 2.5: Performance Intraday Momentum Market Timing Strategy

Intraday Momentum Strategy	Full Sample	Crises
Mean return	0.001%	0.009%
Sharpe	0.426	2.637
Skewness	5.196	7.279
Kurtosis	137.582	131.327
Success rate	49.530%	51.410%

Always Long Strategy	Full sample	Crises
Mean return	0.004%	0.004%
Sharpe	1.261	1.124
Skewness	-5.413	-7.060
Kurtosis	138.342	132.897
Success rate	52.135%	51.193%

This table reports summary statistics on the performance of a market timing strategy based on intraday momentum and an always-long trading strategy. The market timing strategy goes long when the first half-hour return is positive, and short otherwise. The always-long strategy always goes long the last half-hour of the trading day. The results are reported for the full sample and for the crisis periods. We report the mean daily return, the (annualized) Sharpe ratio, skewness, kurtosis, and the success rate.

intraday momentum appears to be more pronounced during crises.

When we restrict the sample to the crisis periods, the strategy performs particularly well. The strategy posts a higher return, a higher Sharpe ratio, and a higher success rate than the always long strategy. Interestingly, the returns to the intraday momentum strategy are again positively skewed, whereas the always long strategy exhibits negative skewness. As such, the intraday momentum trading strategy appears to limit downside risk.

Overall, these findings suggest that, although this fairly naïve strategy does not generate attractive returns overall, the strategy does appear to generate attractive returns in bad market states.

2.5.2 Informed Trading versus Liquidity Provision

Having established the presence of intraday momentum in the RUB-USD market, we explore the likely drivers of intraday momentum outlined in the introduction. As a starting point, we first analyze how volume is distributed over the trading day. We can expect informed traders to execute their trades around the opening and closing of the trading day to take advantage of increased volume and liquidity, if we observe high trading volume in the morning and a pick-up in trading volume again towards the end of the trading day. To investigate whether this is the case, we report the average 30-minute trading volume (in US Dollars) for the different trading hour regimes in Figure 2.2[5].

The figure suggests that volume, on average, does not exhibit a U-shape, as is typical in equity markets (see, e.g., Jain and Joh, 1988). Simultaneously, the box plots indicate that there is nevertheless considerable time series variation in the volume traded during every half-hour of trading. The fact that the RUB-USD market does not exhibit a U-shaped distribution in volume over the trading day has an important implication for the 'informed trading hypothesis'. This observation suggests that, although we find intraday momentum, informed trading may not be the main driver because there is generally no reason for informed traders to postpone their trading to the last half-hour of the trading day. This idea is consistent with the finding of Menkhoff and Schmeling (2010), who, using a short sample of data on the MICEX that includes anonymized trader identifiers, find that informed traders mainly trade during the opening of the trading sessions in the MICEX. Naturally, informed traders may have other considerations in addition to the trading volume for spreading trades over the trading day.

To formally analyze the relationship between intraday momentum, informed trading, and liquidity demand, we estimate several model specifications. To be concise, we focus on the crisis periods, for which we find intraday momentum to be most pronounced[6]. For purposes of comparison, in column (1) of Table 2.6, we first repeat the baseline predictive regression of interest.

In Table A.2 of the Appendix, we observe that intraday momentum is related to the realized volatility and trading volume over the first half-hour of trading[7]. To control for both effects, we include the realized

[5]For completeness, we report similar figures for DPIN and EWQS in the Appendix.

[6]The results for the full sample, reported in Table A.1 of the Appendix, remain qualitatively the same.

[7]Gao et al. (2015) show that intraday momentum is positively associated with volume and volatility. In Table A.2 of the Appendix, we repeat their analysis and find that intraday momentum is positively associated with volume and volatility.

Table 2.6: Disentangling Liquidity and Informed trading During Crises

	(1)	(2)	(3)	(4)	(5)
Variables	r_l	r_l	r_l	r_l	r_l
r_f	0.0656**	0.0608**	0.0954*	0.0071	0.0368
	(0.031)	(0.025)	(0.051)	(0.017)	(0.037)
r_{sl}	-0.2271	-0.2467	-0.2299	-0.2458	-0.2338
	(0.178)	(0.168)	(0.144)	(0.162)	(0.142)
$D_L(DPIN) \cdot r_f$			-0.0447		-0.0354
			(0.059)		(0.056)
$D_H(DPIN) \cdot r_f$			-0.0756		-0.0765
			(0.056)		(0.054)
$D_L(EWQS) \cdot r_f$				0.0136	0.0214
				(0.027)	(0.027)
$D_H(EWQS) \cdot r_f$				0.0642*	0.0671**
				(0.036)	(0.031)
Opening σ^2_{RV}		-0.0955	-0.0941	-0.0925	-0.0902
		(0.078)	(0.070)	(0.075)	(0.067)
Opening $log(Volume)$		-0.0000	-0.0000	-0.0000	-0.0000
		(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.0000	0.0002	0.0002	0.0002	0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	922	922	922	922	922
$R^2(\%)$	15.7	19.0	21.7	20.2	23.0

This table presents regression results for the sub-sample that covers both periods of financial distress, i.e. the financial crisis of 2007-2009 and the Russian crisis of 2014. Column (1) regresses the closing half-hour return (r_l) on the first half-hour return (r_f) and the second last half-hour return (r_{sl}). In column (2), we control for volume and realized volatility during the first half-hour of trading. Column (3) evaluates the impact of informed trading on the closing half-hour return. In column (4) we measure the impact of liquidity on the closing half-hour return. Finally, in column (5) we combine both specifications.

Newey and West (1987) robust standard errors in parenthesis. Significance at 1%, 5%, and 10% level indicated by ***, **, and *, respectively.

volatility during the first half-hour and the (common log of) volume as controls in column (2). Controlling for volume and realized volatility, we observe no change in the sign, magnitude, or significance of the estimated coefficients. For completeness, we report the pairwise correlations between the variables of interest in Table A.3. of the Appendix[8].

Turning to the other specifications, column (3) reports the specification that analyzes the relationship between intraday momentum and periods of low and high levels of informed trading. In particular, we construct a set of dummy variables that equal 1 depending on whether the level of informed trading during the first half-hour is in the top (D_H), middle, or bottom (D_L) tercile, respectively. We then interact these dummy variables with the observed return during the first half-hour of trading, omitting the middle tercile to serve as the baseline. The coefficients on the interaction terms in column (3) suggest that the predictive relationship is not significantly stronger during periods of above-average or below-average levels of informed trading in the first half-hour of the trading day.

Column (4) analyzes the alternative hypothesis, which relates intraday momentum to liquidity provision by day traders during the start of the trading session. Similar to the case of informed trading, we divide all trading days into three different terciles, depending on the value of the EWQS over the opening half-hour interval. We hypothesize that higher-than-average quoted spreads during the first half-hour of trading are indicative of higher levels of liquidity demand, requiring liquidity provision by some other market participants.

All else being equal, higher quoted spreads can also be the result of high volatility. However, because we include the realized volatility over the first half-hour of trading as a control variable, the regression specification should control for this effect and allow us to better isolate the impact of liquidity provision following strong liquidity demand. In this regression, we also interact the resulting dummy variables with the first half-hour return. Interestingly, we find that the first half-hour return becomes insignificant. Instead, the interaction term that interacts the first half-hour return with the dummy in periods of high quoted spreads becomes positive and significantly so. This finding suggests that intraday momentum is the result of high liquidity demand by market participants during the opening combined with dealers' risk aversion to overnight inventory. Finally, we control for the level of informed trading; see column (5). Menkhoff and Schmeling (2010) find that informed

[8]The pairwise correlation between the equal-weighted quoted spread and the dynamic probability of informed trading is high (0.69). However, the coefficients for the specifications in which we omit one of the two variables (cfr. infra) do not change meaningfully (see Table A.3), suggesting that multicollinearity is not an issue.

traders in MICEX tend to trade when spreads are higher, implying that we need to control for the level of informed trading.

Interestingly, controlling for informed trading, we find that the relationship becomes even more pronounced from a statistical perspective. This result suggests that intraday momentum tends to occur during trading days when quoted spreads are high, even when controlling for the potential effect of informed trading on spreads. We interpret this finding as supportive of the hypothesis that intraday momentum is to a certain extent driven by a high liquidity demand during the morning combined with a strong risk aversion to overnight holdings potentially driven by risk management policies, the disposition effect or habits among market makers.

Are there institutional circumstances that may explain why intraday momentum in the Ruble market appears to be the result of liquidity provision, rather than informed trading? The main differences between foreign exchange and other financial markets are the sheer size of FX markets and the fact that these markets are only accessible by major dealers. We can imagine that, because the FX market is considerably larger in terms of notional value, informed trading is less likely to impact prices. Simultaneously, however, if a sufficiently large fraction of the market's participants reacts similarly to a news announcement, then liquidity demand can be expected to meaningfully impact prices (albeit temporarily)[9].

Second, the results suggest that the traders who provided liquidity to these early trades close their positions and thus take exactly the same direction as the information-driven trades at the start of the day. Because these traders mirror the information-based trades in the morning, what is their motivation and why do they not adjust their behavior?

We note that microstructure theory suggests that the bid-ask spread consists of three components: an order processing component, an adverse

[9] A second reason why liquidity may be the prime driver of intraday momentum is the following. Informed traders attempt to hide their informational advantage through splitting large orders (Chordia and Subrahmanyam, 2004) into several smaller, medium-sized transactions (Chakravarty, 2001). Thus, their trading will be geared towards avoiding a meaningful price impact. To the extent that traders are successful at hiding their informational advantage, we will not observe any intraday momentum. Moreover, although excess inventories require trading near the end of the trading day, the informed trading hypothesis provides no rationale for informed traders to always trade in both the morning and the afternoon. Because informed traders want to monetize their informational advantage as quickly as possible (Bloomfield et al., 2005), it is less likely that they will want to wait until the end of the trading day, especially, in markets as deep as FX markets. Moreover, earlier work using the same data on the same market concludes that FX traders on the MICEX mainly trade during the opening session through medium-sized orders (Menkhoff and Schmeling, 2010).

selection component, and an inventory holding component (Huang and Stoll, 1997). Changes in the spread, in this case, are likely to be driven by changes in the latter two components[10].

One reason why the intraday pattern, if it is indeed driven by liquidity provision during the opening session, may continue to exist is the following. We can assume that, when market makers set their prices, they will most likely take into consideration the ease with which they will be able to eliminate the position again. As such, a market maker will be willing to provide liquidity provided that the premium (i.e., the inventory holding component) received is higher than the likely cost of having to liquidate the position again later that day. In other words, the profit from providing liquidity during the first half-hour should offset the expected loss from forced liquidation later that trading day. This may explain why the effect persists and why traders who generate the effect continue to survive.

2.5.3 Robustness Checks

We now present the results of additional regressions to test the robustness of the intraday momentum effect on several dimensions. In particular, we analyze whether the effect is robust across different subsamples, different return sampling frequencies, alternative definitions of liquidity, and changes in the estimation method.

2.5.3.1 Subsample Analysis

We repeat the analysis for both crisis periods separately. If intraday momentum in the RUB-USD market is indeed primarily a crisis phenomenon, we expect to observe a significant relationship during both crisis periods identified above. We report the results for the Global Financial Crisis of 2007-2009 and the Russian crisis of 2014 in Panels A and B of Table 2.7, respectively.

Although the relationship is significant in both instances, intraday momentum appears to be especially pronounced during the Russian crisis of 2014. This finding should not come as a surprise, given that the Russian Ruble was to a large extent the object of the crisis. This was not

[10]The order processing component refers to market makers' fixed costs. The adverse selection component compensates the market maker in cases when he or she is trading against a counterparty who may have superior information. For example, aggressive (market) orders may indicate that the counterparty has private information and thus may motivate the market maker to increase the spread. Finally, the inventory holding component refers to a premium that the market maker requires for providing liquidity during periods of unbalanced flows.

Table 2.7: Robustness Check - Global Financial Crisis (2007-2009) & Russian Crisis (2014)

	Panel A: Financial Crisis (2007-2009)			**Panel B: Russian Crisis (2014)**		
Variables	r_l	r_l	r_l	r_l	r_l	r_l
r_f	0.0214*		0.0214*	0.0926*		0.0820**
	(0.012)		(0.012)	(0.051)		(0.039)
r_{sl}		0.0053	0.0045		-0.4832	-0.3836
		(0.066)	(0.066)		(0.376)	(0.271)
Intercept	0.0001**	0.0001**	0.0001**	-0.0001	-0.0001	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	686	686	686	236	236	236
R^2 (%)	1.4	0.0	1.4	19.7	12.3	27.2

This table represents the results for the sample period January 10, 2007 to December 30, 2009 and January 10, 2014 to December 30, 2014 by regressing the closing half-hour return (r_l) on the first half-hour return (r_f) and the second last half-hour return (r_{sl}). Panel A contains the results for the financial crisis (2007-2009), panel B contains the results for the Russian crisis (2014). Newey and West (1987) robust standard errors in parenthesis. Significance at 1%, 5% and 10% level indicated by ***, **, and *, respectively.

Table 2.8: Robustness Check - Sensitivity of Intraday Momentum to the Return Frequency

r_f/r_l	60m	30m	15m
60m	0.0457**	0.0667*	0.0245*
30m	0.0513**	0.0698*	0.0269**
15m	0.0214	0.0330*	0.0273**

This table presents regression results for the return frequency sensitivity analysis. The coefficients for the specification under Eq. (2) for alternative opening and closing return frequencies are displayed.
Significance using Newey and West (1987)standard errors at 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.

the case during the Global Financial Crisis of 2007-2009, where equity and credit markets played the leading part.

2.5.3.2 Choice of the Return Frequency

The use of half-hour returns strictly follows earlier work on intraday momentum in financial markets. However, this usage leaves unanswered the question of whether the peak of momentum predictability indeed is situated around this particular frequency. A natural question that arises is whether the observed intraday momentum is robust to the use of different frequencies[11]. To test whether intraday momentum is sensitive to the frequency and whether half-hour returns are the peak of the observed predictability, we re-run the regression in Eq. (1) for different combinations of return frequencies. In particular, we perform $K \times K$ regressions to analyze all potential combinations of the first and final 15-minute, half-hour, and one-hour returns. We report the coefficients of interest in Table 2.8.

We find that intraday momentum is robust to the frequency employed. In particular, the price action at the start of the trading day is predictive of the price evolution near the end of the trading day, and the relationship is robust to the particular interval chosen. In economic terms, the effect is strongest for opening half-hour returns on closing half-hour returns.

Next, we analyze the robustness of the main results to a change in frequency. Because both proposed mechanisms that may drive intraday momentum can be expected to be at play especially during the very start

[11] We thank an anonymous referee for calling attention to this point.

and end of the trading session, we re-run the main analysis, calculating all variables of interest over the first 15 minutes of trading, and try to predict the return during last 15 minutes of the trading session. The first column of Table 2.9 reports the results.

Our findings continue to hold, indicating that the mechanism that drives intraday momentum is at play at the very start of the trading session.

2.5.3.3 Alternative Liquidity Measures

Next, we assess the robustness of our main results to different measures of liquidity. To that end, we repeat the specifications in Table 2.6 using several alternative measures of liquidity that we can construct from the data we have at our disposal. First, we turn to the Effective Spread (ES) as the liquidity metric. The result is shown in column (2) of Table 2.9 and confirms our baseline results and the results described above. In particular, we continue to find that liquidity appears to be the main driver of intraday momentum in the RUB-USD FX market.

Second, we replace the EWQS variable from our baseline analysis with the Volume-Weighted Quoted Spread (VWQS). This measure weights the bid-ask spreads by the volume of trades, and therefore, it takes into consideration the size of the trade matching the observed bid and ask prices. We report the result in column (3) of Table 2.9. Here too, we find that the intraday momentum effect is stronger when bid-ask spreads are high during the opening half-hour interval.

2.5.3.4 Estimation method

The estimations we have performed so far are based on OLS. Return series, however, tend to exhibit volatility clustering, which, from a statistical perspective, induces heteroscedasticity. In addition, high-frequency data often exhibit significant levels of negative autocorrelation over very short intervals (Roll, 1984) and positive autocorrelation over slightly longer intervals. Some of these patterns are the result of microstructure-related issues such as the bid-ask bounce, whereas others follow from the fact that information processing takes time (see Chordia et al., 2005). Using Newey and West (1987) robust standard errors, we have so far accounted for such effects on the estimation results.

Nonetheless, because we do not know the full shape of the distribution of the data, we re-estimate the main results using the Generalized Method of Moments (GMM). Although the moments we impose are identical to the moments under OLS, a two-step GMM allows us to efficiently estimate the model when we face heteroscedasticity and autocorrelation

Table 2.9: Robustness Check - Alternative Definitions and Estimation Method

Variables	(1) r_l	(2) r_l	(3) r_l	(4) r_l
r_f	0.0031	0.0507	0.0418	0.0368
	(0.019)	(0.036)	(0.038)	(0.036)
r_{sl}	-0.0826	-0.2285	-0.2312	-0.2338*
	(0.088)	(0.143)	(0.142)	(0.141)
$D_L(DPIN) \cdot r_f$	0.0035	-0.0413	-0.0346	-0.0354
	(0.020)	(0.058)	(0.055)	(0.055)
$D_H(DPIN) \cdot r_f$	-0.0307	-0.0743	-0.0763	-0.0765
	(0.027)	(0.055)	(0.054)	(0.054)
$D_L(EWQS) \cdot r_f$	0.0193			0.0214
	(0.019)			(0.027)
$D_H(EWQS) \cdot r_f$	0.0398**			0.0671**
	(0.018)			(0.031)
$D_L(ES) \cdot r_f$		0.0165		
		(0.037)		
$D_H(ES) \cdot r_f$		0.0491*		
		(0.027)		
$D_L(VWQS) \cdot r_f$			0.0049	
			(0.027)	
$D_H(VWQS) \cdot r_f$			0.0623**	
			(0.030)	
Opening σ^2_{RV}	-0.0827*	-0.0919	-0.0902	-0.0902
	(0.047)	(0.069)	(0.067)	(0.067)
Opening $log(Volume)$	-0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.0003	0.0002	0.0002	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	922	922	922	922
$R^2(\%)$	11.3	22.2	23.0	

This table reports the results for a number of robustness checks. Column (1) reports the results of the main specification using an alternative return frequency of 15-minutes for the first- and last half-hour return. Column (2) presents the results using the effective spread as a measure of liquidity. Column (3) similarly presents the results using the Volume-Weighted Quoted Spread as a liquidity measure. Finally, column (4) reports the results obtained from estimation of the main specification using two-step GMM.

Newey and West (1987) robust standard errors in parenthesis in column (1) through (3). Significance at 1%, 5%, and 10% level indicated by ***, **, and *, respectively.

of an unknown form. We report the result in the final column of Table 2.9. The result indicates that our findings are robust to the particular estimation method employed.

2.6 Conclusion

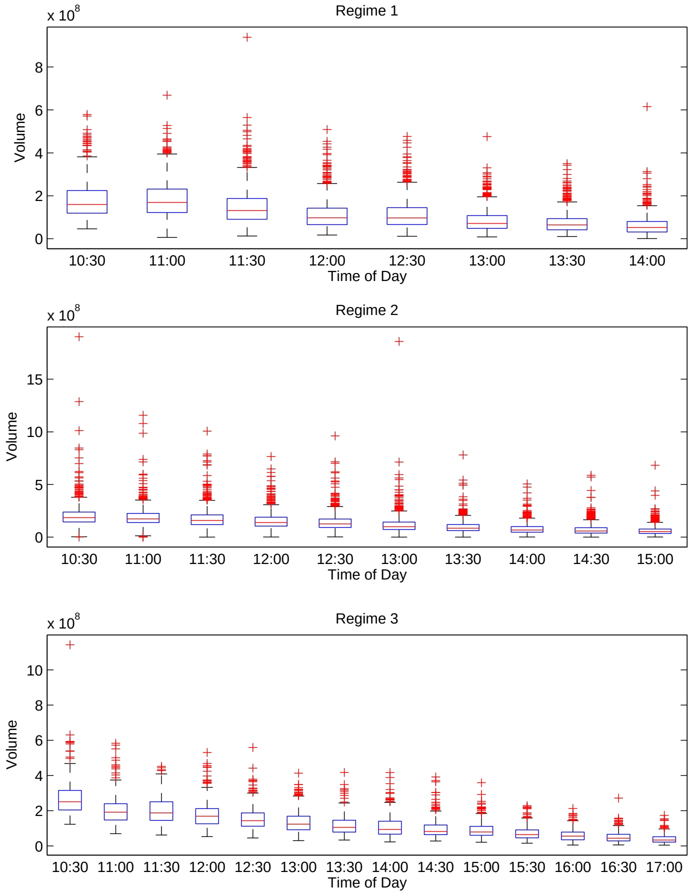
In this paper, we use a long sample of transaction-level data at tick frequency on the Russian Ruble-US Dollar currency pair from the MICEX to investigate the likely drivers of intraday momentum in this FX market.

We contribute to the emerging literature of momentum at the intraday level in several ways. First, we find no evidence that intraday momentum in the Ruble market is the result of market participants' strategic trading during high-volume periods. Two observations motivate this conjecture. First, there is no reason for informed traders in the Ruble market to postpone trading until the last half-hour of trading, given that volume in the market does not exhibit a U-shape intraday pattern. This is consistent with earlier work by Menkhoff and Schmeling (2010), who find that informed traders on this particular market mainly trade during the opening of the trading session. Second, we do not find a stronger intraday momentum pattern on days with more informed trading in the first half-hour of trading.

Instead, we find evidence that closing half-hour returns are positively related to opening half-hour returns on days when spreads in the Ruble market are high during the opening half-hour. These high spreads are consistent with a strong liquidity demand by market participants in the first half-hour of trading. This finding lends support to the argument that dealers and other liquidity providers in the Ruble market are trying to offload unwanted inventories (Lyons, 1995;Bjønnes and Rime, 2005) due to their risk aversion to overnight holdings. This interpretation is consistent with the empirical finding of Bjønnes et al. (2005), who show that non-financial customers are the main liquidity providers in the overnight foreign exchange market.

Second, we provide additional evidence that corroborates the finding of Gao et al. (2015) that explicit trading hours matter for intraday momentum. The particular nature of the RUB-USD FX market, a currency pair for which spot trading is only possible on the MICEX, provides a unique case where FX trading is subject to explicit trading hours. Finally, our results lend further support to the finding that intraday momentum is more pronounced during crises.

Figure 2.2: Distribution of Volume (in US Dollars) over the Trading Day



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Chapter 3

The Components of Interdealer Spot FX Bid-Ask Spreads during Periods of Calmness, Crisis, and Interventions[1]

3.1 Introduction

There is a wide body of literature dealing with the estimation of bid-ask spreads of securities (Roll, 1984; Glosten, 1987) and their decomposition into various components. Several likely components of bid-ask spreads have been brought forward. First, the literature stresses the importance of the order processing component. This component serves to compensate market participants for costs incurred (e.g. wages, rent, IT-infrastructure) needed in order to handle the transaction. Second, early (theoretical) models on spread decomposition (Stoll, 1978; Amihud and Mendelson, 1980) highlight the presence of dealers and potential strategies they use to optimize their inventory of securities. These models bring forward the inventory holding component in the spread. This component serves as a means of protecting against holding unwanted amounts of inventory and as a compensation for tying up capital. Third, other (theoretical) models focus on the information content of trades (Kyle,

[1] This chapter is based on joint work with Michael Frömmel (Ghent University).

1985; Glosten and Milgrom, 1985; Easley and O'Hara, 1987). As such, this strand of the literature brings forth a third element referred to as the adverse selection component, that compensates liquidity providers from being picked off by more informed market participants.

Much of the theoretical work on spread decomposition models is based on the particular structure of the New York Stock Exchange (henceforth, NYSE) (Glosten and Harris, 1988; Huang and Stoll, 1997). The NYSE is built around specialists (market makers) who create a market by providing quotes – bid and ask prices – to other market participants. As such, the NYSE is a quote-driven market. Models analyzing such a market structure stress the importance of dealers' inventory management and behavior. In contrast, the foreign exchange market differs radically from quote-driven markets since it has a decentralized structure and is more opaque. More specifically, while the quote-driven market still largely applies to the second tier of the foreign exchange market in which clients trade bilaterally with their dealers providing quotes, this is not the case for the first tier. Yet, the first tier lies at the heart of how foreign exchange markets are structured. It is this tier that covers the vast majority of FX trading volume (Lyons et al., 2001) and where dealers trade directly with each other, either bilaterally or indirectly (e.g. voice brokerage) or via electronic brokers (i.e. EBS limit order book).

In this paper, we employ data that corresponds to trading on the first tier of the Russian Ruble-US Dollar (henceforth RUB-USD) foreign exchange market. The interdealer RUB-USD market is facilitated through an electronic platform in which dealers place limit or marketable limit orders to the electronic trading platform. These orders then jointly form the limit order book. As such, this interdealer market is quite centralized. All the bid and ask quotes, transactions, volume, and order flow are visible to market participants that have direct access to the Moscow Interbank Exchange (MICEX) platform. Given these market characteristics, we rely on the modified decomposition model of McGroarty et al. (2007). In their model, they assume that informed traders are setting prices through limit orders (Bloomfield et al., 2005; Goettler et al., 2009) instead of actively exploiting superior information through market orders. This spread decomposition model modifies the established spread decomposition model of Huang and Stoll (1997) in their baseline assumption of how information is incorporated into the observed price which makes the model better suited for order-driven markets. We contribute to the existing literature in at least three ways. First, we are the first to apply a modified version - adjusted to order-driven markets -

of a well-established model to the first tier of an emerging FX market[2]. Second, due to data availability issues as a consequence of the nature of high frequency, the analysis in previous literature is limited to a few days or months at most. We in contrast are able to analyze the spread components over a period of almost five years, which allows us to examine the time variation. Third, recent developments, namely the recent Russian currency crisis, enable us to observe how spreads and spread components evolve and how they are affected during periods of market stress. Given the particular nature of our emerging market data set, we expect the adverse selection component to contribute considerably. Furthermore, we expect that the adverse selection component increases in periods of turmoil like the Russian Ruble currency crisis in 2014. Our results indicate that a significant part of the bid-ask spread (approximately 45%) compensates market participants against adverse selection. At the same time, the relative importance of the adverse selection component seems to decrease over time. This indicates more widespread information and lower uncertainty due to better market coverage. During the Russian crisis of 2014, we observe market participants asking a higher compensation (in absolute terms) against adverse selection. At the same time, the relative importance of the adverse selection component of the bid-ask spread does not increase during crisis periods. This appears to be neither the case for the full year, nor within the year. As for the (temporary) buy-sell order imbalance component (inventory holding), we find this to be a significant part of the spread (19%), albeit smaller compared to the adverse selection component. The relative importance of the buy-sell order imbalance component also seems to be declining year on year, with the notable exception of the Russian crisis in 2014. Especially, during the last two months of 2014 – when the crisis reached a peak – we observe a strong increase in the order imbalance component.

The remainder of this paper is structured as follows. In section 2 we describe the data used for our empirical analysis. Section 3 presents the applied methodology for decomposing the spreads. Section 4 provides and discusses the results. We conclude in section 5.

[2] Russian Ruble-United States Dollar exchange rate which corresponds to the second most important BRICS-currency representing about 1.6% and 1.1% of total FX trading volume in 2013 and 2016 respectively (BIS, 2016).

3.2 Data

3.2.1 Data description

We collect data on the first tier of an emerging foreign exchange market, in which dealers can submit limit- or marketable limit orders to a centralized trading platform. More specifically, we use unique, intraday tick-by-tick transaction data on the RUB-USD provided by the MICEX[3]. To shed light on the global importance and compare the RUB-USD currency pair to other major currency pairs, we note that spot trades in the RUB-USD currency pair equal 1.6% of total FX spot trading volume in 2013 and 1.1% in 2016, ranking it as the 12th and 17th mostly heavily traded currency pair for each period separately. This drop in importance could possibly be attributed to the Russian currency crisis and accompanied economic sanctions. Moreover, the RUB-USD's importance has increased from a total of FX trading volume of 0.30% in 1998 to 1.1% in 2016, making it the second most traded BRICS-currency (Bank for International Settlements, 2016). The period for which we are able to obtain data covers the period from January 12, 2000 to December 30, 2014. Our data set contains the following set of information for every trade executed on the MICEX, a time-of-day time stamp, the price at which the order was effectively executed, and the Dollar volume of the trade. Additionally, the data set contains information on the trade initiator, but only from November 2010 onwards. For this reason, we restrict the sample period to November 2010-December 2014. Figure 3.1 describes the evolution of the RUB-USD exchange rate over the (full) sample period.

The total yearly volume traded in US Dollar increases year after year till 2012 after which it has reached a yearly volume of more than 400 billion USD as shown in Figure 3.2 .

In Table 3.1 we report summary statistics for our data set. Overall, we observe that the returns are considerably negatively skewed, have a very high kurtosis, and exhibit negative first order serial correlation. On average, the returns are very close to 0 and are characterized by a low standard deviation.

[3]MICEX is the largest exchange in Russia and Eastern Europe. For foreign exchange markets, MICEX centralizes country-wide domestic USD-RUB trading on one single platform. This platform has been jointly developed with Reuters and provides similar trading features as for the Reuters or EBS (Electronic Brokerage Systems) trading platform.

Figure 3.1: Evolution of the RUB-USD Exchange Rate

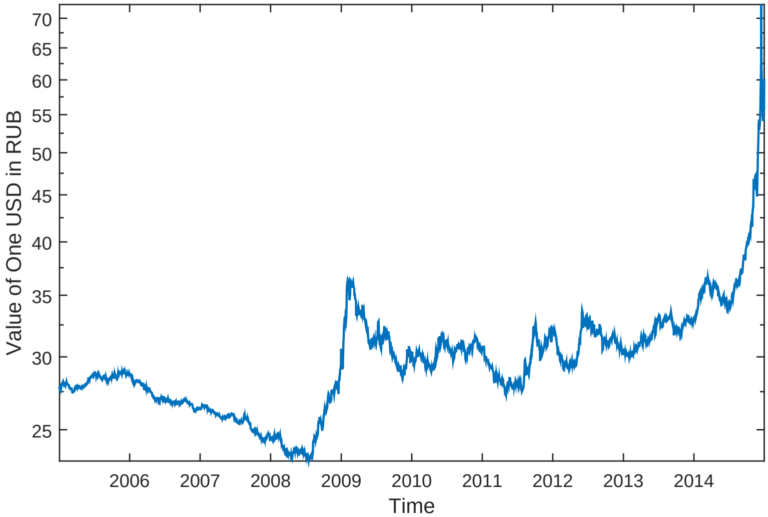


Figure 3.2: Evolution of the RUB-USD Traded Volume

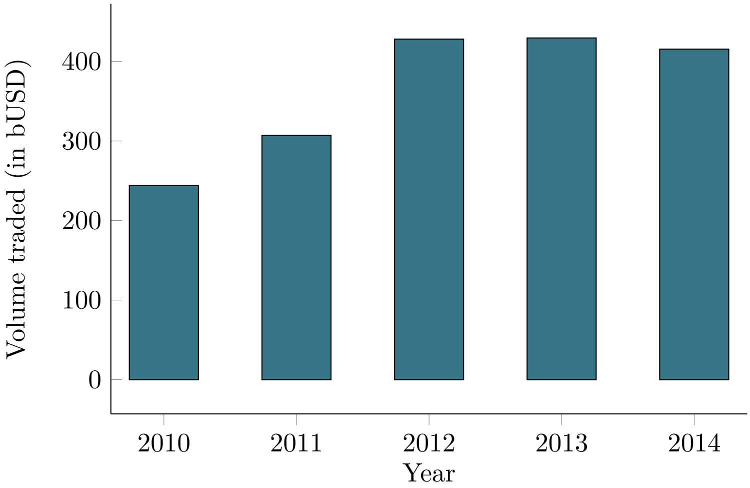


Table 3.1: Summary Statistics

Time Period	Full Sample	2010	2011	2012	2013	2014
Mean	-0.011%	0.024%	-0.008%	0.005%	-0.005%	-0.027%
Median	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
Min	-10.506%	-1.056%	-2.571%	-3.544%	-1.623%	-10.506%
Max	10.356%	0.973%	2.143%	2.172%	2.906%	10.356%
Standard Deviation	0.020%	0.018%	0.017%	0.013%	0.008%	0.029%
Skewness	-6.540	-0.215	-3.716	-10.716	18.843	-5.388
Kurtosis	33013	1197	3501	9076	20467	20402
First order serial correlation	-0.164	-0.318	-0.210	-0.138	-0.202	-0.157

This table reports the summary statistics of the logarithmic return (*1000) over the chosen data sample, both for the full sample as for each year separately.

3.2.2 Foreign exchange policy

Given our specific data set it should be noted that in the past decades, the Bank of Russia changed their exchange rate policy several times. In 1999, the Bank of Russia introduced a managed floating exchange rate regime, aimed at smoothing exchange rate fluctuations. In order to ensure flexibility of monetary policy in their inflation targeting strategy, they gradually decreased the central bank's influence on the exchange rate. Interventions, if any, were exclusively performed in US dollar. Later on, the managed float was replaced by a dual-currency basket in 2005, consisting of US dollar and Euro. Accordingly the Bank of Russia intervened in both currencies to limit excessive dual-currency basket value fluctuations. Shifts in the operational band were performed considering the balance of payment dynamics and domestic FX market developments. Over time, the Euro became more important for the Russian economy and the Bank of Russia fixed the basket at 0.55 USD and 0.45 EUR in early 2007. Most interestingly for our data set, the Russian central bank gradually increased the width of the band in the course of the financial crisis and abandoned the dual currency basked in late 2010. Since then the Bank of Russia conducts an FX policy under a managed floating exchange rate regime still with a dual currency basket, but without imposing a formal band, while using interventions to smooth exchange rate fluctuations. Based on these policy shifts we conjecture that interventions in absence of a formal band aimed at smoothing exchange rate fluctuations increase information asymmetries and thus adverse selections costs since these actions contain a surprise element. On the other hand, these interventions ease and restore (temporary) market imbalances and thus decrease the (temporary) buy-sell order imbalance component of the bid-ask spread.

3.3 Methodology

There has been a wide body of literature on the estimation of spreads (Roll, 1984; Glosten, 1987), the components of spreads, and spread decomposition models trying to estimate them. These spread decomposition models can be separated into covariance based approaches (George et al., 1991; Stoll, 1989) and trade indicator based approaches (Glosten and Harris, 1988; Madhavan and Smidt, 1991; Huang and Stoll, 1997). One of the most prominent trade indicator based model used for decomposing spread is the Huang and Stoll (1997) model with the two-way decomposition model being most parsimonious model. Thus model allows researchers to estimate the order processing component and jointly the adverse selection and inventory holding component. The three-way spread decomposition of Huang and Stoll (1997) on the other hand, allows us to decompose the spread further. Specifically, the three-way decomposition model allows us to estimate the order processing component, the inventory holding component, and the adverse selection component separately.

$$\begin{cases} \Delta P_t = \frac{S}{2} \cdot Q_t + (\alpha + \beta - 1) \cdot \frac{S}{2} \cdot Q_{t-1} - \alpha \cdot \frac{S}{2} \cdot (1 - 2\pi) \cdot Q_{t-2} + e_t \\ Q_t = (1 - 2\pi) \cdot Q_{t-1} + u_t \end{cases} \tag{3.1}$$

Where ΔP represents the price change, Q_t indicates the direction of a trade at time t, S represents the bid-ask spread, α equals for the (estimated) adverse selection cost, β represents the inventory holding component, and π is the probability that the next transaction has the opposite sign as the current transaction. The model above has as disadvantage that it requires a simultaneous estimation of these two equations, making it far from parsimonious. Second, the literature has documented some estimation problems related to the parameter π. Huang and Stoll (1997) argue that the too low estimation of π results from an observed positive serial correlation in price changes which may be due to market participants' decision of breaking up an order into several smaller orders. They argue that the aggregation of these sliced orders provide an adequate solution to induce negative serial correlation, allowing a correct estimation of a trade reversal probability. Henker and Wang (2006), however, show that the low and negative adverse selection estimates (α) in Huang and Stoll (1997) their three-way decomposition model are the result of model misspecification. Another, perhaps more important issue in light of the current paper, is the fact that the Huang and Stoll (1997) 2-and three-way decomposition model are developed for quote driven markets, i.e. centered among a market maker. McGroarty et al. (2007) alter this viewpoint and build a spread decomposition model specifically designed for order-driven markets such as foreign exchange markets. In their model, the authors argue and assume that informed traders are setting prices through limit orders (Bloomfield et al., 2005; Goettler et al., 2009) instead of actively exploiting superior information through market orders. As a result, the fundamental value, V_t, is now only driven by its past fundamental value and newly discounted public information.

$$V_t = V_{t-1} + \varepsilon_t \tag{3.2}$$

At the same time, (temporary) buying or selling pressures could temporarily induce the price to diverge from the true fundamental value.

Therefore, the distorted fundamental value, V_t^* is a function of (true) fundamental value and any (temporary) buy-sell order imbalances, Q, in the market

$$V_t^* = V_t + \beta \cdot \frac{S}{2} \cdot \sum_{i=1}^{t-1} Q_i \tag{3.3}$$

The midquote, M, is affected both by the distorted fundamental value and the information content expressed by the adverse selection component (α) as informed traders are submitting limit order. As such, they jointly determine the appropriate midquote as follows

$$M_t = V_t^* - \alpha \cdot \frac{S}{2} \cdot Q_t \tag{3.4}$$

Taking everything together, the above model boils down to the following price equation in which the price, P, is affected by the fundamental value, the (temporary) buy-sell order imbalance (β) on the market, and adverse selection component (α)

$$P_t = V_t + \beta \cdot \frac{S}{2} \cdot \sum_{i=1}^{t-1} Q_i - \alpha \cdot \frac{S}{2} \cdot Q_t + \frac{S}{2} \cdot Q_t + \eta_t \tag{3.5}$$

Differencing this equation leads to the following equation, which resembles to the (Huang and Stoll, 1997) decomposition model

$$\Delta P_t = (1 - \alpha) \cdot \frac{S}{2} \cdot Q_t + (\alpha + \beta - 1) \cdot \frac{S}{2} \cdot Q_{t-1} + e_t \tag{3.6}$$

If quote data is available, then the model can be estimated as it is exactly identified. In that case the above equation evolves to the following, more parsimonious model in which the reversion indicator π, is no longer required

$$\Delta P_t = (1 - \alpha) \cdot \frac{S_t}{2} \cdot Q_t + (\alpha + \beta - 1) \cdot \frac{S_t}{2} \cdot Q_{t-1} + e_t \tag{3.7}$$

3.4 Results

We start off by discussing some summary statistics on spreads and transactions in panel A of Table 3.2. In particular, we report the time series of the average spread as well as average number of daily transactions both for the full as sample as for each year separately. Overall, we observe that the average number of transactions increases on a yearly basis. The average quoted spread in contrast, decreases year after year. The only exception is 2014, during which the bid-ask spread increased considerably following heightened uncertainty during the Russian crisis. Following the state-of-art in the literature, we estimate the spread decomposition model using GMM (Hansen, 1982). This way, we can account for the very weak distributional assumptions and potential heteroscedasticity and autocorrelation of an unknown form. The results, as shown in panel B of Table 3.2, clearly indicate a statistically significant adverse selection component (α) in the bid-ask spread. This is both the case for the full sample as when we estimate each year separately. Overall, we observe that the adverse selection component equals approximately 45% over the full sample. This result is in line with our expectations, since we are considering an emerging foreign exchange market. Compared to previous studies on non-major currencies, our findings are in line with Bjønnes and Rime (2005) who find an adverse selection component of 49% for the NOK-DEM. Our results, however, stand in contrast to Frömmel and Van Gysegem (2012) who only find an adverse selection component of 21% on the HUF-EUR market. Second, we find that the relative importance of the adverse selection component decreases year after year, from 74.92% in 2010 to 44.41% in 2014 which indicates a growing market coverage.

Even in 2014 during the Russian crisis, the adverse selection component did not increase at all in relative terms. In absolute terms, we also report a decrease in the adverse selection component year after year, except for 2014 (Figure 3.3). From this figure, we can clearly illustrate that the uncertainty during the Russian crisis of 2014 increases market participants' perceived probability of being picked off by a market participant with superior information. As a result, such uncertainty raises the adverse selection component of the bid-ask spread. Taking this all together, we conclude that the absence of observing an increase in the relative importance of the adverse selection component during the crisis is not due to the lack of higher requirements of protection against adverse selection but caused by the higher lift in the other two spread components.

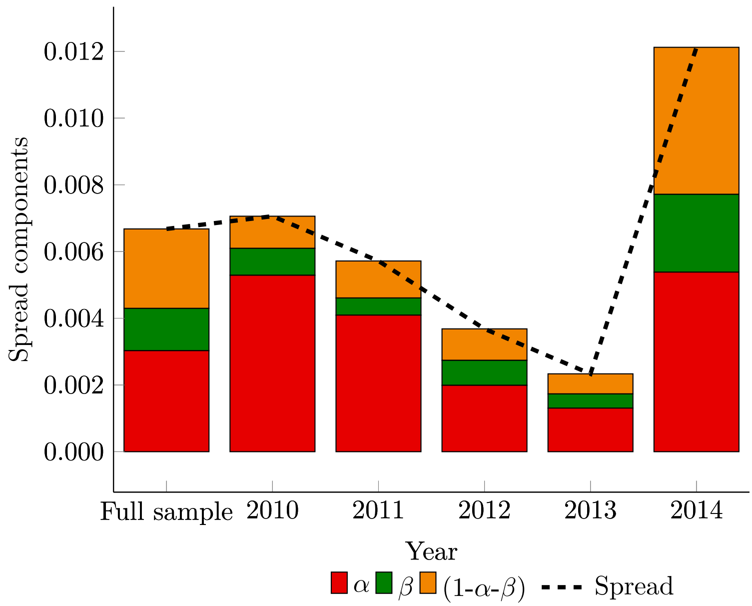
The (temporary) buy-sell order imbalance component is significantly positive both for the full sample, 18.96% with a p-value of 5.1%, as well as for every year separately. Overall, we find that the relative importance of the (temporary) buy-sell order imbalance component seems to increase over time (Figure 3.3), from around 10% until 2012, to about 20% thereafter. We could possible attribute this to the changing Russian central bank policy striving towards a fully-floating exchange rate regime henceforth, the market becoming more mature. As a result, exchange

Table 3.2: Bid-Ask Spread Components

Time Period	Full Sample	2010	2011	2012	2013	2014
Panel A: Summary Statistics						
Avg. Spread	0.006678	0.007059	0.005717	0.003682	0.002334	0.012122
Avg. Daily Trans.	2771.6	1642.8	1817.4	2533.9	3319.1	3553.2
N	2,712,924	45,970	432,286	605,353	789,684	839,631
Panel B: Relative Value of the Spread Components						
α	0.4535***	0.7492***	0.7161***	0.5405***	0.5596***	0.4441***
se(α)	(0.058558)	(0.009929)	(0.012069)	(0.020014)	(0.022294)	(0.062347)
β	0.1896*	0.1142***	0.0899***	0.2031***	0.1826***	0.1923*
se(β)	(0.097238)	(0.011239)	(0.026662)	(0.025961)	(0.039947)	(0.104518)
(1-α-β)	0.3569	0.1366	0.1940	0.2564	0.2578	0.3636
Panel C: Components of the Average Quoted Spread						
α	0.003029	0.005289	0.004094	0.001990	0.001306	0.005383
β	0.001266	0.000806	0.000514	0.000748	0.000426	0.002331
(1-α-β)	0.002383	0.000964	0.001109	0.000944	0.000602	0.004408

This table presents the various spread components of the Russian Ruble-United States Dollar exchange rate from 22nd of November 2010 till the end of December 2014. Panel A reports the average quoted spread, average daily transactions and the total amount of observations both for the full sample as for every year separately. Panel B reports the 2-step GMM-estimates. This contains the adverse selection component (α), the (temporary) buy-sell order imbalance component (β), and the price-clustering component (1-α-β) with respective robust standard errors in parenthesis. Panel C reports the absolute value of each component. Significance at 1%, 5% and 10% level are indicated by ***, ** and * respectively.

Figure 3.3: Absolute Importance of the Bid-Ask Spread Components

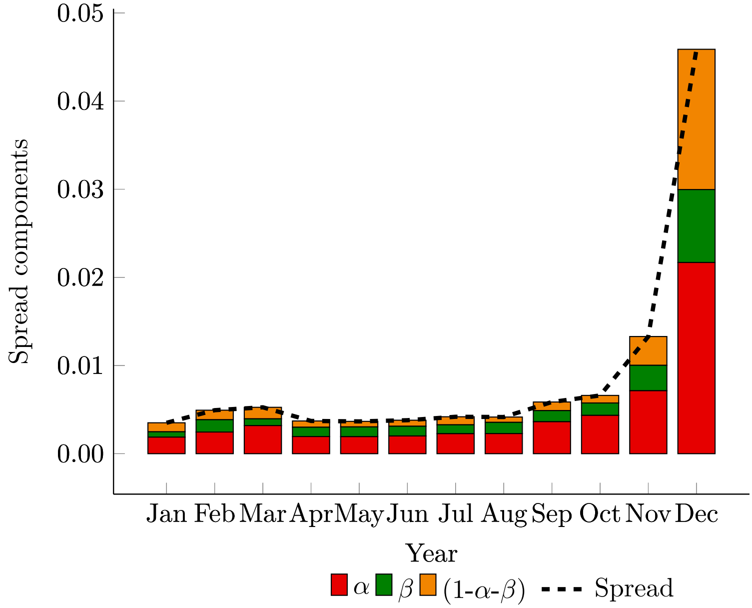


rate interventions happen both less frequent and with less firepower. As such, increased price-concessions are required when many market participants are trading in the same direction and the central bank is less willing to apply a leaning-against-the-wind policy to stabilize the exchange rate. This becomes more apparent in the Russian crisis of 2014 where many market participants likely wanted to offload or even short the Russian Ruble. This action could have contributed to the increase the (absolute) inventory component to 0.002331. This is on average four times higher than before and resembles 19.23% of the spread, and let the exchange rate surge to unexplored heights. The residual part, i.e. the price-clustering component, contributes 35.69% to the spread over the full sample period. Year on year, we find an increasing relative importance (Figure 3.3) of this component, especially during 2014.

3.4.1 Spread Components during the Russian Crisis

Next, we zoom in on the Russian crisis and examine whether the spread and its components change markedly during periods of high stress. We do this by running the same model separately for every month for in 2014. The results, reported in panel B of Table 3.3, clearly indicate

Figure 3.4: Absolute Importance of the Bid-Ask Spread Components during Crisis (2014)



that during times of crisis, the adverse selection cost (α) contributes significantly to the full bid-ask spread. More specifically, we find the adverse selection component to be significantly positive every month at the 1% level of significance, remaining relatively stable and ranging between 47.28% and 65.77%. With respect to the composition of the bid-ask spread, we do not find evidence that the adverse selection component contributes more to the spread during highly uncertain periods (53.75% in November and 47.28% in December) versus non-crisis periods. This finding is somewhat unexpected. Still, we find a small increase in the adverse selection component before the crisis (61.85% in September and 65.77% in October) reached its full proportion.

The absolute values of the spread (see Figure 3.4) in contrast, clearly illustrate the effect of the crisis on the spread and its components. The effect of the crisis began to materialize slowly in September 2014 and resulted into a higher spread as 2014 progressed. Each component, however, seems to have contributed to a similar extent to the increase in the bid-ask spread. In November and December 2014, the bid-ask spread began to increase significantly, indicating that liquidity providers were starting to ask considerably more protection against adverse selection.

Table 3.3: Bid-Ask Spread Components in Crisis Times (2014)

	January	February	March	April	May	June	July	August	September	October	November	December
Panel A: Summary Statistics												
Avg. Spread	0.003504	0.004934	0.005260	0.003712	0.003663	0.003796	0.004187	0.004158	0.005864	0.006607	0.013291	0.045876
Avg. Daily Trans.	3635.5	2993	3247.35	2857.0909	3205.3333	3088.5263	3009.2273	2850	2934.7619	3543.7273	5195.1875	6274.619
N	58168	56867	64947	62856	57696	58682	66203	59850	61630	77962	83123	131767
Panel B: Relative Value of the Spread Components (With Standard Errors)												
α	0.5360***	0.4979***	0.6063***	0.5234***	0.5275***	0.5295***	0.5425***	0.5488***	0.6185***	0.6577***	0.5375***	0.4728***
se(α)	(0.049867)	(0.014706)	(0.103424)	(0.025308)	(0.010197)	(0.015191)	(0.014559)	(0.015359)	(0.027380)	(0.022485)	(0.069941)	(0.037415)
β	0.1727*	0.2833***	0.1453	0.2851***	0.3016***	0.2903***	0.2397***	0.3054***	0.2152***	0.2125***	0.2166	0.1803***
se(β)	(0.085745)	(0.012739)	(0.152221)	(0.036212)	(0.016957)	(0.021900)	(0.025097)	(0.025005)	(0.033510)	(0.046622)	(0.115810)	(0.054346)
(1-α-β)	0.2913	0.2188	0.2484	0.1915	0.1709	0.1802	0.2178	0.1458	0.1663	0.1298	0.2459	0.3469
Panel C: Components of the Average Quoted Spread												
α	0.001878	0.002456	0.003189	0.001943	0.001932	0.002010	0.002271	0.002282	0.003627	0.004346	0.007144	0.021690
β	0.000605	0.001398	0.000764	0.001058	0.001105	0.001102	0.001004	0.001270	0.001262	0.001404	0.002879	0.008272
(1-α-β)	0.001021	0.001079	0.001307	0.000711	0.000626	0.000684	0.000912	0.000606	0.000975	0.000858	0.003268	0.015915

This table presents the various spread components of the Russian Ruble-United States Dollar exchange rate during the 2014 crisis period. Panel A reports the average quoted spread, average daily transactions and the total amount of observations both for the full sample as for every year separately. Panel B reports the 2-step GMM-estimates. This contains the adverse selection component (α), the (temporary) buy-sell order imbalance component (β), and the price-clustering component (1-α-β) with respective robust standard errors in parenthesis. Panel C reports the absolute value of each component. Significance at 1%, 5% and 10% level are indicated by ***, ** and * respectively.

At the end 2014 when the crisis began to reach its full proportions, the (temporary) buy-sell order imbalance component (absolute) grew to 0.002879 and 0.008272 in the last two months which is four and eight times higher than before and partly explains the observed increase in the bid-ask spread. In relative terms, this component is lower and not higher than usual. We attribute this particular result to the Russian central bank that was fiercely supporting the exchange rate by selling USD for RUB. As such, a major market participant was standing on the other side therefore reducing the order imbalance on the market. Therefore, this component is in relative terms smaller during the midst crisis when the central bank was intervening than before when they were not.

3.5 Conclusion

This papers examines the bid-ask spread components by applying the spread decomposition model of McGroarty et al. (2007) build for an order driven market. We apply the model over a long-time span for the RUB-USD, a previously unexplored foreign exchange market data set. We find a decline in the bid-ask spread year on year. Except for the Russian crisis in 2014, the spread has grown to much larger proportions. Furthermore, in line with previous work on spread decomposition (Bjønnes and Rime, 2005) we find that overall, 45% of the spread can be attributed to adverse selection, although the relative importance of this component is decreasing year on year. This suggests that an increase in market coverage is taking place, making information more widespread and thereby decreasing uncertainty. Moreover, we observe an increased demand for protection (in absolute terms) against adverse selection during the Russian crisis in 2014. This finding is mostly driven by the final months of 2014 when the crisis became full-fledged. However, somewhat unexpectedly, the relative importance of the adverse selection component does not increase during periods of high uncertainty.

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Chapter 4

The Accuracy of Trade Classification Systems on the Foreign Exchange Market: Evidence from the RUB-USD Market[1]

4.1 Introduction

In many financial applications it is crucial to know whether the initiator of a trade was the active or the passive trader. A formal definition of the term trade initiator is primordial if one wants to assess the accuracy of trade classification systems. An explicit definition of the term 'initiator' is nonetheless hardly ever given in the literature. Odders-White (2000) distinguishes two definitions, first the immediacy definition sees traders who demand immediate execution as the initiators. Traders who placed market orders or limit orders at the quotes, which essentially is the same, are thus tagged as initiators, while traders who placed limit orders are viewed as non-initiators or passive suppliers of liquidity[2]. Second, the

[1] This chapter is based on joint work with Dick D'Hoore and Michael Frömmel (Ghent University).

[2] There are few cases in which this definition is problematic: when crossed market orders are executed, when limit orders are matched with each other and when market orders are stopped. All cases occur frequently on financial markets, according to the study by Lee and Radhakrisna (1996), this is the case in 12%, 17% and 29%

chronological definition which is broader. The trader, both buying or selling, who placed his or her order last is the initiator. These two definitions are similar in many cases, as the initiator always causes the transaction to occur. However, the latter can certainly be applied with crossed market orders, a limit order matching another limit order and stopped market orders. This definition is often used for markets where no market maker or specialist is present to provide liquidity, thus for interbank foreign exchange markets. Knowing who is the trade initiator is crucial for two key concepts in market microstructure: order flow and bid-ask spreads. Order flow is defined as the difference between trades initiated by the buyer and trades initiated by the seller of a currency, thus the sum of signed transactions. The order flow can be described as buying or selling pressure, shows a close empirical relation to the exchange rate (Lyons et al., 2001; Evans and Lyons, 2002; Payne, 2003) and carries private information (Frömmel et al., 2008). From the definition of order flow, it is clear that knowing whether the initiator of a transaction is buying or selling is of crucial importance to the outcome of these studies. For the estimation of the bid-ask spread components, Huang and Stoll (1997) used methods based on a trade indicator variable. Peterson and Sirri (2003) did the same for the accurate calculation of effective spreads. Empirical applications include testing for the presence of informed traders (Easley et al., 1996), measuring the information content of trades (Hasbrouck, 1991) and intraday momentum (Elaut et al., 2016). Unfortunately, most data sets do not contain the trade direction hence inferring who initiated the trade has always been complicated, even more so in today's high frequency setting. That is why many researchers use trade classification systems to determine who is buying and who is selling.

Although some research has been conducted in the efficacy of trade classification systems, most of them focus on equity markets. The foreign exchange market on the other hand has not yet been covered to the same extent and some questions remain unanswered. Our contribution to the literature is twofold: first, we add to the recent literature by comparing popular available trade classification systems on real world data. The set of trade classification rules we compare is extraordinarily broad and covers all relevant approaches that have been suggested so far. Second, we assess the accuracy of the various trading indicator classifiers for a foreign exchange market. As Theissen (2001) points out, and is reflected in the literature review later in this manuscript, markets' microstructure substantially affects the accuracy of trade classification systems. In other words, a different market structure changes the "game played by the

respectively on the NYSE.

market participants" (Rime, 2003, p471). It is therefore necessary to analyze trade classification rules for different markets.

The foreign exchange market substantially differs from equity markets, which is covered by the vast majority of empirical contributions on trade classification rules. It is decentralized, but highly concentrated in London and New York, has no designated market makers, is self-regulated, and has no margins and no short sale restrictions (Omrane and Welch, 2016). It is a two-tier market, separated into the interbank market, where on the one hand professional currency traders deal with each other and where price discovery takes place, and on the other hand the customer market, where customers trade with the banks and submit their orders, which are finally executed on the interbank market. Since the mid-1990s electronic communication networks have emerged as a subset to the customer market, as a formalized way for customers to trade with each other. Some ECN focus on small corporations, others on retail investors (Rime, 2003). Due to their lack of liquidity most ECN are crossing networks, i.e. they obtain prices from other trading venues without own price discovery. At the same time, the trading volume on the foreign exchange market by far exceeds the one of all other markets, with a daily turnover of about 5.1 trillion USD (Bank for International Settlements, 2016). In addition, the foreign exchange has a strong impact on the real economy (King et al., 2011) hence it is highly relevant for the real economy.

Studies having trade initiator classified data of the foreign exchange market are extremely rare, only few data sets with signed data have been exploited in the literature (Omrane and Welch, 2016). In their study they use data from an ECN[3], which is a network designed for non-reporting dealers and has very specific characteristics. In addition, their data set covers two years whereas our data set covers 3.5 years of the interbank market. Furthermore our study applies a far broader range of trade classification rules than Omrane and Welch (2016).

The rest of the paper proceeds as follows. Section 4.2 introduces the various classification rules and discusses their performance in past literature. Section 4.3 describes the characteristics of the RUB/USD market and the data. Section 4.4 describes the applied methodology, section 4.5 discusses the results and section 4.6 summarizes and concludes.

[3]As Omrane and Welch (2016) state, "ECN data has poorer classification success across all the algorithms and because of the dominance of electronic markets today, recent studies like Chakrabarty et al. (2007) are perhaps more relevant."

4.2 Trade Classification Rules (TCR)

The research concerning trade classification algorithms or trade classification systems is not very elaborate, nor is it very old. While Blume et al. (1989) and Hasbrouck (1988) were the first to apply trade classification rules, Lee and Ready (1991) were the first to systematically compare and analyze the performance of TCRs. In general we can distinguish trade-by-trade classification rules, which assign a binary value (buyer- or seller-initiated) to every single observed trade and bulk-classification rules, which assign a probability for being buyer- or seller-initiated to a bulk, defined by time, volume, or amount of trades. In this section we will first briefly introduce the most commonly used TCRs, before we review the literature on performance evaluation for TCRs.

4.2.1 Trade-by-trade classification rules

The Tick rule (Blume et al., 1989) is the simplest TCR, as it only requires transaction data. It is based on the price movements relative to the preceding trades. If the current price is higher (an uptick), then the trade is classified as a buy. If the current price is lower (a downtick), the trade is classified as a sell. In the special case that no price change occurs, it is the last prior uptick or downtick that is taken into consideration[4]. The functioning of the tick rule is displayed in Figure 4.1. A variation on the tick rule is the Reverse Tick rule. The current price is compared to the following price, instead of the preceding price. If the following price is higher (lower), the current trade is classified as a sell (buy). As long as the price follows a price reversal pattern, i.e. B(uy)-S(ell)-B(uy)-S(ell), both rules yield the same results. The classification will differ, as soon as there are sequential price movements in the same direction, e.g. B-B-S-S. The literature generally doubts the effectiveness of this RTR rule and therefore it is rarely used.

The Quote rule defined by Hasbrouck (1988) uses more information as it obviously relies on quote data. Transactions above the spread midpoint, entailing those at the ask, are classified as buys. Transactions below the spread midpoint, entailing those at the bid, are classified as sells[5]. Transactions at the spread midpoint remain unclassified[6].

[4] Lee and Ready (1991) call this a 'zero-uptick', or 'zero-downtick', depending on whether the last price change was upwards or downwards.

[5] In the so-called 'at-the-quote rule trades are only classified when they occur at the best ask or bid price. The rules is rarely used, since it substantially restricts the available data.

[6] Lee and Ready also proposed a '5 second rule'. In that time, quotes were updated on a computer inside the specialist's post, while the trade was typically recorded by the specialist's clerk. It could occur that the quotes were updated faster than the

The Lee and Ready rule (LR rule) is in fact a combination of tick rule and quote rule. Lee and Ready (1991) suggest to apply the quote rule where possible, and use the tick rule to classify the trades at the midpoint, which are left unclassified by the quote rule. This was based on the quote rule performing better outside the midpoint, whereas the tick rule was able to classify 85% of the trades at the midpoint correctly (Lee and Ready, 1991). Due to its good performance and simple implementation the LR rule is one of the most widely used TCR. When applying the LR rule to data from the NASDAQ Ellis et al. (2000) observed a bias (i.e. a consistently reduced accuracy) in the classification of large trades, trades during high volume periods and ECN trades. They attributed this bias to the classification of trades executed inside the quotes. Accordingly, they proposed the EMO rule[7]Ellis et al. (2000), which slightly differs from the LR rule since it relies more on the tick test. They wanted to address the reduced accuracy of the classification of trades inside the quotes. Therefore only trades at the quotes are categorized using the quote rule, while all the trades inside the quotes are categorized based on the tick rule.

A variant of the former rule is the MEMO rule as suggested by Chakrabarty et al. (2007). It differs from the EMO rule by classifying trades using the quote rule for all trades executed at the bid (ask) or 30 percent of the spread above the bid (below the ask), whereas the tick rule is used for the 40 inner percent of the spread.

Figure 4.1 illustrates the various trade-by-trade classification rules. It is obvious that for the first four trades, characterized by a zig-zag pattern and trades performed at the quote the rules show no difference. Differences between the TCRs occur as soon as trades within the quotes occur. For this reason the market structure is an important feature for assessing the accuracy of TCRs. Trades with conflicting signals from the TCRs are shaded in grey.

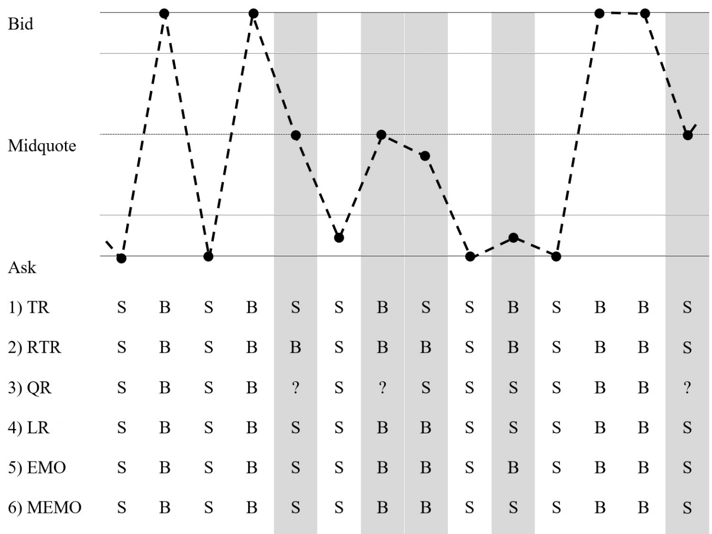
4.2.2 Bulk Volume Classification

While the research on traditional trade-by-trade TCR dates back 25 years to the first extensive study done by Lee and Ready (1991), no real radical changes have occurred ever since. TCR remained combinations of a quote rule and a tick rule, with research showing better results for

transactions that triggered them. This could lead to an incorrect classification and it is thus unsuitable to compare the quotes and trades. They demonstrated that if the execution prices are compared to quotes reported at least 5 seconds before the trade was reported, superior results were achieved. Their argument, however, does obviously not apply to modern FX trading.

[7]In their paper Ellis et al. (2000) refer to it as the quote-tick rule.

Figure 4.1: Illustration of trade-by-trade rules



the more recent EMO and MEMO rules. The performance increase is rather incremental which explains why the easy-to-use TR is still used extensively. The proposition of Easley et al. (2016) to rethink the way TCR are used to discern the underlying information from the data can thus be seen as revolutionary. The Bulk Volume Classification (BVC) allocates a bulk of trades into buy and sell order flow, which is obviously very different to assigning an individual trade as either a buy or a sell. Easley et al. (2016) regard the rise of big data and the resulting ever increasing need to process large data as an important issue, which may seriously strain the resources (both time and hardware) of researchers, and question the need to know the true initiators for every single trade. That's why they propose the BVC, a new TCR that replaces previous discrete trade-by-trade TCR with a continuous classification of probabilistic nature, more closely resembling a Bayesian approach by providing the probability of an outcome. Namely, BVC allocates a bulk of trades into buy and sell order flow. This is very different to assigning an individual trade as either a buy or a sell. This is done by using trade volume over either fixed time, volume or trades intervals. Next, the standardized price change between the beginning and the end of the interval is calculated to estimate the share of buy and sell volume. It should be intuitively clear that the larger (more positive) this price change is, the more probable that the underlying trades were buyer initiated and vice versa. Overall, they conclude that the BVC is superior to the incumbent TCR on index and commodity futures data, both in accuracy and resource requirements.

As an example, suppose the following sequence of 10 trades with true initiator known: BBSSBBSSBB. A trade-by-trade TCR could classify these trades as BSBBSBBSBS, which would give an accuracy of only 40%. The Bulk Accuracy Ratio (BAR) is defined as the fraction of overall volume correctly classified within bars. A bar is a aggregation of trades that occur within a given time period (e.g. one hour), the volume traded (e.g. 10 000 000 USD) or the amount of trades that occurred (e.g. 1000 trades). The formula to calculate the BAR is as follows:

$$BAR = \frac{\sum_{\tau} \left[\min\left(V_{\tau}^{B}, \bar{V_{\tau}^{B}}\right) + \min\left(V_{\tau}^{S}, \bar{V_{\tau}^{S}}\right)\right]}{\sum_{\tau} V_{\tau}} \tag{4.1}$$

Where V_{τ} equals the total volume, V_{τ}^{B} and V_{τ}^{S} represent the true buying and selling volume and $\bar{V_{\tau}^{B}}$ and $\bar{V_{\tau}^{S}}$ represent the predicted buying and selling volume in interval τ. For our example, in the following case we find the following BAR:

$$BAR = \frac{\sum_{\tau} \left[\min\left(6, \bar{6}\right) + \min\left(4, \bar{4}\right)\right]}{10} = 100\% \tag{4.2}$$

Note that if the amount of aggregation increases, more offsetting happens between individually misclassified trades. To calculate predicted buying and selling volume the following formulas are used:

$$V_{\tau}^{B} = V_{\tau} \cdot CDF_{t}\left(\frac{P_{\tau} - P_{\tau-1}}{\sigma_{\Delta P}}, df\right) \tag{4.3}$$

$$V_{\tau}^{S} = V_{\tau} \cdot \left(1 - CDF_{t}\left(\frac{P_{\tau} - P_{\tau-1}}{\sigma_{\Delta P}}, df\right)\right) \tag{4.4}$$

Where t equals the cumulative distribution function (CDF) of a Student´s t-disctribution with *df* degrees of freedom, $P_{\tau} - P_{\tau-1}$ price change between consecutive bars calculated as the difference between the last price of the current bar and the last price of the preceding bar and $\sigma_{\Delta P}$ equals the standard deviation of the price changes.

4.2.3 The Performance of TCR

A couple of studies empirically test the performance of TCRs. These studies however, focus almost exclusively on equity and commodity markets. Furthermore, they are often restricted to a subset of TCRs. Nonetheless, we review some of the existing empirical literature in this section and summarize the findings in Table 4.1.

In their seminal paper, Lee and Ready (1991) test he performance of their own LR rule and find that it correctly classifies trades on the NYSE with a 90.9% success rate. In their data set the share of trades at the quote was 60.6%, while 22.8% were at the midpoint. The rest was inside or – in 0.5 percent of the cases – outside the spread. Wood and McCorry (1994) analyze the tick rule and find a lower accuracy or 80-82% for the NASDAQ, from which they conclude that the performance highly depends on the market structure. Aitken and Frino (1996) find a 75% success rate for the tick rule (90% for non-zero ticks), when they apply it to data from the Australian Stock Exchange (ASX). The ASX is an order-matching system without a prominent role for a market-maker/specialist. However, their study suffers from some data restrictions: Trades can only occur at bid or ask prices, making it impossible to study the accuracy of the LR algorithm. Since no true trade initiator was available, they used the Quote rule as a proxy. They mimicked the LR study and expressed doubts about the robustness of their results in different markets, after having identified six potential types of classification errors. Also, further analysis provided evidence that a volatile or trending market decreases the accuracy of the tick rule and makes it less likely to accurately classify seller initiated trades and small buyer initiated trades.

Lee and Radhakrishna (2000) study the TORQ data set[8], thus again data from the NYSE. For the 60% of observations which they can classify as either buyer or seller initiated, they report a success rate of 93% for the LR rule. The same data set and TCR are used by Odders-White (2000). She reports a somewhat lower success rate of 85%, but finds a systematic misclassification by the LR rule for trades at the midpoint, small transactions and large and frequently traded stocks. Consistent with her findings and again for TORQ data, Finucane (2000) reports a success rate of 84% for the LR rule compared with an only marginally lower accuracy of 83% for the reverse tick test. He explains the surprisingly good performance of the reverse tick rule by the specific structure of the sample, including market order crosses (16%), stopped market orders (26%), and quote changes between the trades (43%).

Theissen (2001) is one of the few analyzing the accuracy of the LR rule (besides the tick rule) for a non-US market. He uses data from the Frankfurt Stock Exchange and a benchmark classification based on the

[8]The TORQ data set is a subsample of detailed trade data on 144 firms listed on the NYSE. It was collected under supervision of Joel Hasbrouck, see Lee and Radhakrishna (2000).

position taken by the specialist ("amtlicher Kursmakler"). He finds a remarkably low accuracy for both rules (72.2% for the TR and 72.8% for the LR rule) and no statistically significant difference in the accuracy between the rules. He explains the odd results by the existence of the courtage (a commission paid on all trades) and cross-sectional patterns in Makler or specialist participation rates. He concludes that there are large differences in the performance of trade classification algorithms across markets.

Ellis et al. (2000) apply the quote rule, the tick rule, the LR rule and their own EMO rule to data for 313 NASDAQ stocks. They find that the EMO rule outperforms the other rules with an accuracy of 81.9% compared to 76.4% (QR), 77.66% (TR) and 81.05% (LR). However, the improvement over the LR rule is marginal.

Chakrabarty et al. (2007) analyze data from 750 NASDAQ stocks traded on two ECNs (INET and ArcaEx). They apply a wide range of classification algorithms: the tick rule, the Lee and Ready algorithm, the EMO rule suggested by Ellis et al. (2000) and the MEMO rule suggested by themselves. They find that all rules provide accuracies between 74.4% (LR) and 76.5% (MEMO). They do, however stress, that the MEMO rule substantially outperforms the other rules for trades inside the quote.

Few studies analyze the performance of bulk-based classification algorithms. Chakrabarty et al. (2013) compare the bulk-volume-classification (BVC) to the tick rule. They find that the TR clearly outperforms the BVC by 7.4 to 16.3 percentage points, whereas the BVC substantially reduces the computational time by up to 75%. Similarly for data from Euronext Paris, Panayides et al. (2014) find an accuracy for the BVC of up to 90.90% for the average over three different sample periods, whereas the tick rule and the LR rule reach up to 96.57 and 95.79% respectively. Again the advantage of the BVC is rather in terms of computational speed than in accuracy, and the BVC performance increases with bar size.

For a data set of option trades from the CBOE Savickas and Wilson (2003) find a substantially lower accuracy of 59%, 83%, 80% and 78% for the tick rule, quote rule LR rule and EMO rule respectively. They see the high share of reversed quote trades (buys at the bid and sells at the ask) and wrong-side quotes (buys below the bid and sells above the ask) as the main reason for the poor performance.

Lu et al. (2009) apply a modified LR rule to ECN data for 684 stocks from the Taiwan Stock Exchange and achieve an accuracy of 97% (compared with 74%, 93%, and 95% for the tick rule, the quote rule and the EMO rule respectively). Omrane and Welch (2016) recently studied the accuracy of the tick rule and BVC on EUR/USD, JPY/USD and GBP/USD from Hotspot (an electronic communication network). In their data set they deal with asynchronous trade and quote records and therefore the tick rule's performance deteriorates to an accuracy of 65.9%, 69.8% and 66.3% for their three currency pairs. It is thus remarkably low, and even falls substantially for zero ticks. Furthermore they find a strong asymmetry between seller and buyer initiated trades and more specifically they noticed an excessively low accuracy for buyer initiated trades in down quote changes. When they compare the group tick test to BVC (time bars) they confirm the results from other studies and find a superior performance of the tick rule.

Besides pure tests of the accuracy a couple of papers deal with special cases: Asquith et al. (2010) apply the quote rule, the tick rule, and the LR rule to a sample of short sales for 200 NASDAQ stocks and find that short sales are likely to be misclassified as buyer-initiated. In contrast, Chakrabarty et al. (2012) question the assumption that short sales are predominantly seller-initiated and that misclassification is much less of a problem.

The literature has also highlighted biases in trade indicator classifiers that are of relevance the related literature. For example, Boehmer et al. (2007) stress the importance of the trade classification algorithm for estimating the probability of informed trading (PIN). They show analytically that inaccurate trade classification leads to downward-biased estimates for the PIN, The magnitude of the bias is affected by the security's trading intensity. These findings are confirmed by an empirical analysis based on data from the New York Exchange. Finally they propose a data-based adjustment procedure for reducing the bias. Perlin et al. (2014) provide a stochastic version of the tick test that could be used for correcting biases.

4.3 Data

Our study uses transactions and quotes from the US Dollar-Russian Ruble market, and covers the period from mid-2011 to 2014. The RUB/USD rate is one of the more heavily traded exchanges rates: The 'Triennial Central Bank Survey of foreign exchange activity (Bank for International Settlements, 2016) ranks it as the 12th and 17th most important currency pair in 2013 and 2017 and with a share in global turnover of 1.6% and 1.1% respectively. Over the sample period, it is ranked as the second most important currency from a BRICS country (with the Chinese Yuan/US Dollar ranked first) during our sample period. Table 4.2 gives some descriptive statistics of our data set and clearly indicates the increased activity on the exchange.

Table 4.1: Research on the Accuracy of Trade Classification Rules

Author(s)	**Data**	**TCR**	**Accuracy**	**Benchmark**
Lee and Ready (1991)	NYSE	LR rule	90.9%	True classification
Wood and McCorry (1994)	NASDAQ	TR	80-82%	
Aitken and Frino (1996)	ASX	TR	75%	Quote rule
Lee and Radhakrishna (2000)	TORQ (NYSE)	LR rule	93% for classified trades (i.e. 60% of the sample)	True classification
Odders-White (2000)	TORQ (NYSE)	LR rule	85% for LR rule	True classification
Finucane (2000)	144 stocks from TORQ (NYSE)	LR rule and RT rule	84% for LR 83% for RTR	True classification
Ellis et al. (2000)	313 NASDAQ stocks	QR, TR, LR rule, and EMO rule	76.4% for QR 77.7% for TR 81.1% for LR rule 81.9% for the EMO rule	True classification
Theissen (2001)	15 stocks from the Frankfurt Stock Exchange	TR, LR rule	72.2% for the TR 72.8% for the LR rule	Based on the position taken by the specialist (“Makler”)
Savickas and Wilson (2003)	Option trading from CBOE for 826 securities from NYSE and NASDAQ	TR, QR, LR rule, EMO rule	59% for the TR 83% for the QR 80% for the LR rule 78% for the EMO rule	True classification (matched)
Chakrabarty et al. (2007)	750 NASDAQ stocks traded on two ECNs (INET and ArcaEx)	TR, LR rule, EMO rule, MEMO rule	75.4% for TR 74.4% for LR rule 75.8% for EMO rule 76.5% for MEMO rule	True classification
Lu and Wei (2009)	684 TWSE stocks traded on an ECN	TR, QR, LR rule (modified) and EMO rule	74% for TR 93% for QR 97% for modified LR 95% for EMO rule	Matched orders
Chakrabarty et al. (2012)	300 stocks traded on INET	TR and BVC	Time bars: 77.5-94.4% for TR 62.3-78.1% for BVC Volume bars: 80.7-93.5% for TR 67.9-77.8% for BVC	True classification
Perlin et al. (2014)	15 stocks from BOVESPA traded on an ECN	TR	72% for TR	
Panayides et al. (2014)	Continuously traded French stocks from Euronext Paris	TR, LR rule and BVC	Time bars: up to 96.57% for TR up to 95.73% for LR up to 90.90% for BVC Volume bars: up to 96.26% for TR up to 95.79% for LR up to 90.58% for BVC	True classification
Omrane and Welch (2016)	Hotspot data (ECN) on EUR/USD, JPY/USD and GBP/USD	TR, BVC	TR: 65.9% (EUR/USD), 69.8% (JPY/USD) 66.3% (GBP/USD) 57.4-60% group TR 53.5-57.4% (BVC)	True classification
Our study	RUB/USD trades on MICEX	RTR, TR, QR, LR, EMO, MEMO and BVC rule	RTR: 46.42%, TR: 70.58%, QR:85.78% , LR: 86.10%, EMO: 86.26%, MEMO: 86.85% and BVC: 76.50% - 90.45%	True classification

Table 4.2: Descriptive Statistics on our Data Set

	2011	**2012**	**2013**	**2014**
Num	499 779	1 189 595	1 524 877	1 998 651
Max	32.831	34.198	33.504	80.200
Min	27.392	28.834	29.870	33.025
Mean	30.109	31.174	32.009	40.605
Median	30.530	31.180	32.264	36.220
Std	1.502	1.061	0.946	8.124

This table provides summary statistics on the trading activity and price changes over our sample period.

Figure 4.2: Evolution of the RUB/USD Rate during the Sample Period

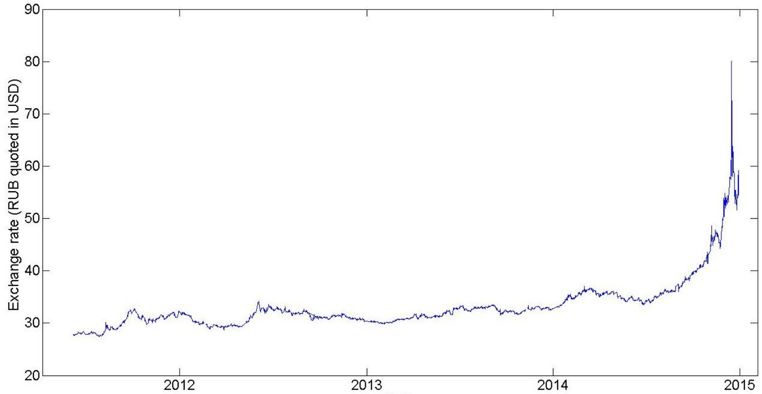


Table 4.3: Sample of the Data Set

Date	Time	Price	Bid	Ask	Buy/Sell
7/06/2011	0.41762	27.835	27.8216	27.8340	1
7/06/2011	0.41762	27.8361	27.8216	27.8340	1
7/06/2011	0.41765	27.8453	27.8280	27.8438	1
7/06/2011	0.41766	27.8281	27.8282	27.8475	-1

This table provides a sample of our intraday dat set which containts for every transaction the accompanying date and timestamp, the best standing quotes and the buy/ sell indicator.

Figure 4.2 displays the evolution of the RUB/USD rate during the sample period. It is obvious that the exchange rate was comparatively stable during the first three years of the sample, with low volatility. In 2014, however, due to the crisis in Ukraine, the deterioration of the oil price and high inflation in Russia, the Ruble sharply depreciated and fell to 80 RUB/USD, whereas the rate between 2011 and 2013 was in the range between 27.392 and 33.504 RUB/USD. Table 4.3 displays a sample of the data set. Time is stored as a fraction of the day, e.g. 0.4172 in the table corresponds to 10:01. Trading starts at 10:00 a.m. and ends at 5.00 p.m. Prices are expressed in Ruble paid or received per one US dollar. Finally the variable Buy/Sell indicates whether the trade was buyer-initiated (+1) or seller-initiated (-1). The fact that the true trade initiator is known, allows us to evaluate the performance of trade classification systems throughout the sample period.

Since the position of the trades relative to the bid-ask spread is important for the evaluation of the TCRs and trades are treated in different ways by the TCRs depending on whether they are at the bid or ask price, inside the spread or at the midpoint, it is worth to take a look at their distribution (Table 4.4). The vast majority of trades (74.1 %) in our sample takes place at the quotes, with 35.4% at the bid and 38.9% at the ask. In comparison to Lu et al. (2009) trades only occur at the quotes, whereas Chakrabarty et al. (2007) use a sample where only 57% of their trades in the ECN take place at the quotes. Furthermore in our sample 15.99% of trades take place inside the quotes, of which only 0.44% happen at the midpoint. Almost 10% of the trades were executed at prices outside the quotes. The ticks are almost evenly distributed between zero and non-zero-ticks. The high number of trades at the quotes in our sample suggest a good performance of TCRs based on the quote rule, i.e. the quote rule itself, the Lee and Ready rule, the EMO rule and the modified EMO rule. However, the respective columns in Table 4.4 show that the distribution has substantially changed over the years and contains there are two interesting observations. First, while in 2011 more than 30% of trades were executed outside the quotes, the fraction dropped in 2012 and 2013 and finally reached 1.54% in 2014. A potential explanation is the increasing liquidity and development of the RUB/USD market. Second, in the crisis year 2014 we observe a huge increase of trades inside the quote, from less than one percent to more than 40%. We will discuss how these features affect the performance of the TCRs.

4.4 Methodology

We test the most widely used trade classification rules on our RUB/USD data set described in section 4.2. Most trade-by-trade rules are in fact combinations of the tick rule and the quote rule. In this respect, the BVC rule is an exception. The accuracy of the trade-by-trade TCR are tested as follows: the predicted trade directions are calculated according to the rules as described in section 4.2.1 and compared with the true classification as given in the data set. The classification can be correct (1) or wrong (0). The percentage of correctly classified trades equals the accuracy of the TCR. Therefore the higher the accuracy, the better the rule is performing. In very few cases no bid or ask prices are available[9], therefore we have excluded these observations from our data set. Comparing BVC with the trade-by-trade classifications is not straightforward, as the latter classifies each trade as either a buy or a sell trade-by-trade, while BVC allocates a bulk of trades into buy and sell volume.

4.5 Results

4.5.1 Tick-by-tick Rules

Table 4.5 summarizes the performance of the trade-by-trade rules over the whole sample period in the first row. It is striking that the RTR substantially underperforms with an accuracy of only 46.42 %. The tick rule correctly classifies only 70.58% whereas the remaining rules all reach an accuracy of more than 85%. While this is lower than what is usually found on equity markets, it is in line with the study by Omrane and Welch (2016) for an FX ECN. They attribute the underperformance of the tick rules to the specific structure of the FX market. The remaining

[9] This applies to 4468 trades in our sample, in which the ask price was missing. For 25 trades of neither the bid nor the ask price was available. On a total of 5,212,902 trades, this corresponds to only 0.0857%.

Table 4.4: Distribution of Trades in the Sample

Location	Obs 2011-2014	2011-2014	2011	2012	2013	2014
Outside quotes	510,790	9.80%	30.39%	13.33%	11.12%	1.54%
Ask	2,025,326	38.85%	33.94%	42.38%	47.26%	31.60%
Bid	1,843,291	35.36%	33.74%	43.84%	41.34%	26.18%
Inside quotes	833,497	15.99%	1.93%	0.45%	0.28%	40.68%
Midpoint	23,128	0.44%	0.03%	0.00%	0.02%	1.13%
Total	5,212,904	100.00%	100.00%	100.00%	100.00%	100.00%
Zero ticks	2,553,135	48.98%	52.58%	52.64%	52.41%	43.32%
Non-zero ticks	2,659,766	51.02%	47.42%	47.36%	47.59%	56.77%

This table provides an overview of the location of trades happening in comparison to the standing quotes.

Table 4.5: Accuracy of Trade-by-trade TCRs

	RTR	**TR**	**QR**	**LR**	**EMO**	**MEMO**
2011-2014	46.42%	70.58%	85.78%	86.10%	86.26%	86.85%
2011	49.10%	62.32%	78.10%	78.11%	75.49%	75.89%
2012	48.62%	66.17%	89.42%	89.42%	89.07%	89.19%
2013	49.36%	68.58%	90.27%	90.27%	90.16%	90.22%
2014	42.21%	76.79%	82.11%	82.93%	84.32%	85.63%

This table provides and overview of the accuracy of the various trade-by-trade classification rules over our sample period as a whole and for every year separately.

rules perform quite similarly with accuracies between 85.78% (QR) and 86.85% (MEMO). The results are in line with Chakrabarty et al. (2007) who find that the MEMO rule performs best, but in our sample the differences are smaller. Furthermore our accuracy is similar to studies based on NYSE data (Lee and Radhakrishna, 2000; Odders-White, 2000; Finucane, 2000), but better than those for NASDAQ data (Ellis et al., 2000; Chakrabarty et al., 2007) and the Frankfurt Stock Exchange (Theissen, 2001). The relatively small improvement of the LR, EMO and MEMO rules over the quote rule can be explained by low number of prices inside the spread, including trades at the midpoint. In a second step we analyze how the rules perform under varying market conditions by looking at their accuracy on yearly subsamples. The results are displayed in rows 2-5 in Table 4.5. Indeed the years 2011 and 2014 show remarkable differences. In 2011, which was characterized by a large fraction of trades outside the quotes, all rules but the RTR perform worse than in the other years. For the EMO and MEMO rule, the lower performance of 2011 compared to the next year is up to 14 percentage points. In contrast 2012 and 2013 have been characterized by low volatility and a high share of trades executed at the quotes. Accordingly the accuracy generally increases. In 2014 we observe more than 40% of trades inside the quotes, which again deteriorates the accuracy. Only the tick rule shows a higher accuracy in 2014. While this contradicts the lower performance of the tick rule in volatile and trending markets as found by Aitken and Frino (1996), it may be due to the higher share of non-zero ticks in 2014. Finally, we examine the accuracy of the rules conditional on the characteristics of the trades. More precisely we examine the accuracy separately for the buy and sell side (Aitken and Frino, 1996; Omrane and Welch, 2016), for trades inside the quote (Ellis et al., 2000;

Table 4.6: Accuracy of Trade-by-trade TCRs and Location of the Trades

	TR	QR	LR	EMO	MEMO
Part A: Initiation					
Buy	67,46%	82,91%	83,14%	82,62%	83,55%
Sell	74,78%	89,64%	90,08%	91,17%	91,29%
Part B: Location of the trades					
Inside quotes	69,57%	67,01%	69,00%	69,57%	73,24%
Zero ticks	65,82%	83,80%	84,07%	84,88%	84,74%
Non-zero ticks	75,15%	87,68%	88,04%	87,59%	88,87%
Total	70,58%	85,78%	86,10%	86,26%	86,85%

This table provides an overview of the classification accuracy. Panel A provides data on the accuracy of trade classification rules with respect to initiation. Panel B provides accuracy figures with respect to the location of the trade.

Chakrabarty et al., 2007)[10], and for zero versus non-zero ticks (Aitken and Frino, 1996; Theissen, 2001; Chakrabarty et al., 2007; Omrane and Welch, 2016). The results are displayed in Table 4.6. First, we confirm the asymmetry in buyer and seller-initiated trades found by Aitken and Frino (1996) and Omrane and Welch (2016), with seller initiated trades performing remarkably better than buyer initiated trades (the average difference is 7.46% for all TCR). Second, for all quote based rules we find lower accuracy for trades inside the quotes, whereas the tick rule's performance is not affected. Again our results corroborate with the empirical literature. Third and finally, we find a substantial underperformance of the tick rule for zero tick trades, which is 9.33 percentage points lower than for non-zero ticks, whereas the difference is on average only 3.67 percentage points for the quote based rules.

4.5.2 Bulk Volume Classification (BVC)

We now turn to the evaluation of the BVC. Before we compare it to the tick-by-tick rules as discussed in the previous section, we perform some considerations on the BVC, such as the choice of the bar size and the stand-alone accuracy. The impact of trade bar size on the BVC's accuracy is given in Table 4.7. Note that there is no theoretical guide-

[10]The EMO and MEMO rule were specifically created to cope with this problem and their superior performance should thus imply that this bias is also present in this study. Odders-White (2000) and Theissen (2001) also reported worse performances for trades occurring on the midpoint of the bid-ask spread, which is a specific case of trades occurring inside the quotes. We do, however, not look at trades at the midpoint, because there are too few of them in our sample.

Table 4.7: Accuracy of BVC

Trade bar size	**BVC**
10	76.50%
25	81.96%
50	84.88%
100	86.97%
250	88.72%
500	89.58%
1000	90.10%
2500	90.45%
5000	90.45%
10000	89.87%
20000	89.64%

This table shows the accuracy of the BVC for various trade size bars.

line on how many trades should form one bar but based on our results and taking into account the average amount of trades per day and the decreasing improvements in BVC's performance, bar sizes of 250, 500 and 1000 trades are deemed the most appropriate. The accuracy of the classification rules are in line with the 88.97% to 93.57% found by Easley et al. (2016) but substantial higher than the 71.1% to 78.2% of Chakrabarty et al. (2013).

Second, the accuracy of the BVC depends on the supposed underlying distribution of price changes. Easley et al. (2016) suggest a Student t-distribution with df = 0.25, while Chakrabarty et al. (2013) opt for a normal distribution, noting no significant differences when compared to t-distributions with various degrees of freedom. Table 4.8 compares the accuracy conditional on various distributions. We find that the performance is slightly better for lower degrees of freedom. As a consequence we rely on the same distribution as Easley et al. (2016).

Third, Chakrabarty et al. (2013) express concerns regarding the negative effect of overnight returns on the performance of BVC. That problem does not occur in the analysis by Easley et al. (2016), who use quasi-continuously traded futures contracts. When omitting overnight returns to exclude possible skewed price changes, Easley et al. (2016) do not find qualitatively different performances compared to when overnight returns were included. Table 4.9 shows the effect of overnight returns on BVC in our analysis. Leaving them out increases the accuracy of BVC slightly with 0.08 to 0.11 percentage points, which seems negligible when con-

Table 4.8: BVC and Alternative Distributions

Student t-distribution

Bar size	**Df=0.05**	**0.1**	**0.25**	**0.5**	**1**	**100**	**10000**
250	89.02%	89.03%	88.72%	88.19%	87.60%	86.53%	86.52%
500	90.09%	90.04%	89.58%	88.94%	88.27%	87.07%	87.06%
1000	90.85%	90.72%	90.10%	89.34%	88.55%	87.18%	87.16%

This table show the accuracy of the BVC rule using various bar size crossed with the t-distribution with multiple degrees of freedom.

Table 4.9: BVC and Overnight Returns

Trade bar size	**BVC**	**BVC (excl. overnight returns)**
250	88.72%	88.82%
500	89.58%	89.66%
1000	90.10%	90.21%

This table compares the performance of the BVC when overnight returns are included or excluded.

sidering the disadvantages of increased computational time and loss of data. As such, we confirm the results by Chakrabarty et al. (2013) and do not exclude overnight returns in our analysis.

Fourth, the main advantage of BVC as advocated by Easley et al. (2016) is its resource efficiency and especially time savings. We therefore briefly scrutinize this claim. To fully utilize the power of BVC, it is necessary to work with vendor-compressed data, i.e. data that has already been aggregated in bars by the provider, as in the data set used by Easley et al. (2016). In contrast, when dealing with individual trade data as in the data set used by Chakrabarty et al. (2013) and in our study, this aggregation has to be done first before applying BVC. Table 4.10 displays the computational time in seconds when applying different TCR. If solely the application of the TCR for the signing of trades is considered, as would be the case for vendor-compressed data, we find a duration of 0.22s for BVC and an average of 1.07s for trade-by-trade TCR[11]. This corresponds with a time efficiency ratio of 20.5%, i.e. BVC is five times faster than the average tick-by-tick TCR. However, when the preparatory work of aggregating trades in bars is also considered, the total computational time for BVC becomes 0.58s and the efficiency ratio declines to 54.3%. Chakrabarty et al. (2013) report an efficiency ratio of 25% in their study, which is substantially better than the ratio found here. It can therefore be concluded that although BVC offers some time savings, they are not as extraordinary as suggested by Easley et al. (2016) and further depend on the data available to the researcher.

In a final step we compare the BVC to the incumbent trade-by-trade TCRs. As already discussed, this comparison requires to adapt the trade-by-trade TCR so that they also aggregate the classifications in bars. As this allows for offsetting, the BAR or the fraction of overall

[11]Since these computational times can be slightly differ for different runs, they should only be seen as a rough indications for the sake of comparison.

Table 4.10: Computational Time for the Alternative TCRs

	BVC	**TR**	**QR**	**LR**	**EMO**	**MEMO**
Aggregation	0.3617					
Signing	0.2199	1.2864	0.8520	0.8837	1.0159	1.3186

This table shows the time required for executing various trade classification rules.

volume correctly classified within bars of all TCR are then comparable. Table 4.11 displays the results. The BVC does not increase the accuracy over aggregated trade-by-trade TCRs: its performance is slightly worse than the one from the tick rule, but clearly outperformed by the quote-based rules. The findings by Easley et al. (2016) are quite similar, but they conclude that the underperformance is acceptable in the light of the BVC's other advantages. Chakrabarty et al. (2013) report much larger performance differences.

4.6 Conclusion

This paper reviews the literature on trade classification rules and applies them to a unique data set of tick-by-tick trades in the Russian Ruble-US dollar market traded on the MICEX. This is the first evaluation of TCRs on the FX interbank market and at the same time the most exhaustive comparison of TCRs. The accuracy of tick-by-tick rules in our data set are in line with existing literature. The MEMO improved on all previous TCRs and is currently the best choice for classifying trades. When quote data is not present, the TR yields a considerably lower accuracy. Its ease-of-use makes it nonetheless very useful for many researchers. Yearly variations in the accuracy can be attributed to the difference in the location where trades have occurred. Not surprisingly, trades executed at the quotes are the most informative for buy/sell intention. Furthermore, the most important biases encountered in literature have been confirmed in this study: seller initiated trades perform remarkably better than buyer initiated trades. The EMO rule, and especially the MEMO rule, offer substantial improvements over LR as they have far more power for classifying trades that occurred inside the quotes. The biggest disadvantage of the TR is its poor performance for zero ticks. The recently suggested BVC, a TCR that uses bulk classification instead of trade-by-trade classification performs best with a t-distribution and a degree of freedom of 0.25, but still slightly underperforms tick-by-tick rules. With regard to resource efficiency, time savings when using BVC are considerable, but less so when the available data is not yet vendor-

Table 4.11: Performance of BVC vs. Trade-by-trade TCRs

Trade bar size	**BVC**	**TR**	**QR**	**LR**	**EMO**	**MEMO**
250	88,72%	89,79%	92,17%	92,09%	92,41%	92,25%
500	89,58%	90,68%	92,36%	92,25%	92,62%	92,39%
1000	90,10%	91,22%	92,48%	92,34%	92,78%	92,48%

This table compares the performance of the BVC with the various trade-indicator classification rules for various sizes of data aggregations.

compressed and thus has to be aggregated first. Altogether, for our data set all quote-based rules perform similarly well, with the MEMO rule providing the highest accuracy.

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