Frömmel and Kadioglu *Financial Innovation* (2023) 9:95
https://doi.org/10.1186/s40854-023-00500-7

Financial Innovation

RESEARCH

Impact of trading hours extensions on foreign exchange volatility: intraday evidence from the Moscow exchange

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Abstract

Using transaction-level tick-by-tick data of same- and next-day settlement of the Russian Ruble versus the US Dollar exchange rate (RUB/USD) traded on the Moscow Exchange Market during the period 2005–2013, we analyze the impact of trading hours extensions on volatility. During the sample period, the Moscow Exchange extended trading hours three times for the same-day settlement and two times for the next-day settlement of the RUB/USD rate. To analyze the effect of the implementations, various measures of historical and realized volatility are calculated for 5- and 15-min intraday intervals spanning a period of three months both prior to and following trading hours extensions. Besides historical volatility measures, we also examine volume and spread. We apply an autoregressive moving average-autoregressive conditional heteroscedasticity (ARMA-GARCH) model utilizing realized volatility and a trade classification rule to estimate the probability of informed trading. The extensions of trading hours cause a significant increase in both volatility and volume for further analyzing the reasons behind volatility changes. Volatility changes mostly occur after the opening of the market. The length of the extension has a significant positive effect on realized volatility. The results indicate that informed trading increased substantially after the opening for the rate of same-day settlement, whereas this is not observed for next-day settlement. Although trading hours extensions raise opportunities for more transactions and liquidity in foreign exchange markets, they may also lead to higher volatility in the market. Furthermore, this distortion is more significant at opening and midday. A potential explanation for the increased volatility mostly at the opening is that the trading hours extension attracts informed traders rather than liquidity providers.

Keywords: Volatility, Trading hours extension, Foreign exchange market, Informed trading, Volume, Spread, Market overlap, Information flow

JEL Classification: E44, E58, F31, G14, G15

Introduction

The organization of financial markets determine the "rules of the game" (Biais et al. 2005), based on which, both informed investors and (implicit) market makers base their decisions. Therefore, the impact of changes in the market structure on liquidity, volatility, and price formation is of crucial importance for market participants, operators of exchanges, and regulators. Such changes are relatively rare events and usually happen only once, or a few times over a couple of years. Therefore, market players have to base their evaluation of potential changes on research analyzing how these or similar changes have affected the market in the past and serve as a guideline for future adjustments of market organization. Accordingly, empirical research has investigated the effects of changes in the market structure, such as the introduction of call auctions (Agarwalla et al. 2015; Inci and Ozenbas 2017), changes in the call auction design (Park et al. 2022), tick-size reduction (Hsieh et al. 2011), or trading hours extensions.

Some studies have examined the effect of trading hours extensions on intraday returns or volatility in stock and futures markets (Barclay and Hendershott 2003; Fan and Lai 2006; Houston and Ryngaert 1992; Kadioglu 2021; Lee et al. 2009; Miwa 2019; Miwa and Ueda 2017). These studies documented that trading hour extensions have a negative impact on price efficiency. However, even though the foreign exchange (forex) market is the world's largest financial market in terms of turnover and of substantial importance to the economy,[1] to the best of our knowledge, no studies have investigated the effect of trading hour extensions on the forex) market.

First, the forex market substantially differs from equity markets; It is a two-tier market, separated into the interbank market, where professional currency traders deal with each other and where price discovery takes place, and the customer market, where customers trade with banks and submit their orders, which will finally be executed on the interbank market. There are no designated market makers, and the trading activity moves around the globe every day since most of the trading platforms are open 24 h a day. However, there are regional trading platforms using the same technology as the global ones, which have dedicated trading hours, such as the Moscow Exchange (MOEX, formerly MICEX, Moscow Interbank Currency Exchange). Trading hours extensions for these markets are extremely rare. While these local exchanges at first sight seem to be less relevant, they can be of substantial importance for the respective currency. In 2018 the MOEX accounted for 68% of the worldwide Ruble-Dollar and 78% of the Ruble-Euro trading[2] and is the primary liquidity center for the Russian Ruble (RUB). Price discovery in this currency mainly takes place on the MOEX.

Second, different from equity markets, ultra-high frequency data for the forex market is harder to obtain and the available data sets are usually short and cover a few days to weeks, sometimes months.

In summary, although analyzing the effect of trading hours extensions on forex markets can provide crucial feedback to market regulators, trading platform operators, and practitioners, and despite its overwhelming importance, empirical evidence is non-existent. Our motivation is therefore to close this gap and provide the first study on effects of trading hours extensions on the forex market.

To do so, we use an extraordinary data set from the MOEX which is both extremely long and detailed, an exceptional combination. Different from existing data for other

[1] As King et al. (2012) point out, "it would be hard to overstate the importance of foreign exchange markets for the world economy. They affect output and employment through real exchange rates. They affect inflation through the cost of imports and commodity prices. They affect international capital flows through the risks and returns of different assets. Exchange rates are justifiably a major focus for policymakers, the public, and of course the media.".

[2] These figures were retrieved from the MOEX website on 8 March 2023 (https://www.moex.com/s1094).

markets, we use a sample of ten years, which includes six trading hours extensions[3] and therefore provides high statistical power. To the best of our knowledge, there is no other market and no more recent period for the MOEX or any other market with a similarly high number of trading hours adjustments. Besides its length and depth, another advantage of our data set is the fact that we can observe two different instruments: tick-by-tick data of the same-day (as a proxy of the spot market) and next-day settlement (as a proxy of the futures market) of the RUB against the US Dollar (USD) exchange-rate contracts traded on the Moscow Exchange Foreign Exchange Market segment during the sample period. The bilateral RUB/USD rate is selected over the RUB/EUR since the volume trading exceeds that of the latter by a factor of almost 8. Owing to its role for the settlement of energy and other commodity exports the RUB/USD rate has always been much more important in terms of volume and economic significance.

We do not aim to explain the exchange rate dynamics during this period. Instead, we seek to shed light on the impact of trading hours extensions on the forex market (for those platforms that are not open 24/7) from a more general perspective. This means we are concerned with general trading hours, the exchange rate properties nexus, rather than with explaining market dynamics for a particular period. The results reveal that extending trading hours led to a statistically significant increase in the historical volatility of both same- and next-day settlement of the RUB/USD rate in both 5- and 15-min intraday levels after the trading hours extensions. We find the highest increase in volatility when the market opens, and the lowest increase when it closes. The results regarding realized volatility, derived using the autoregressive moving average -autoregressive conditional heteroscedasticity (ARMA-GARCH) model, also indicate that the volatility of the RUB/USD exchange rate increased significantly following an extension of trading hours on MOEX. Additionally, the duration of the trading hours extension significantly affects realized volatility. This study determines a significant, positive relationship between realized volatility and the duration of a given trading hours extension. These findings are valid for both 5- and 15-min intraday levels as well as various measures of volatility. Additionally, trading hour extensions caused an increase in volume and a decrease in the spread in all day and midday time and resulted in an increase in volume and spread at opening time.

The rest of this paper is organized as follows. "Literature review" section provides an overview of the related literature while "Data and methodology" section describes the data and describes the methodology. "Results" section presents and discusses the results. Finally, concluding remarks are presented in "Conclusion" section.

Literature review

Although no research has analyzed the effect of trading hours extensions on the forex market by focusing on direct extensions, a limited number of studies examine the stock market. Houston and Ryngaert (1992) conclude that reductions in NYSE trading hours had a slight impact on return volatility and trading volume. Barclay and Hendershott (2003) find that market prices are less efficient after extending trading hours

[3] The MOEX extended trading hours 3 times (extended from 13:30 to 17:15) for the same-day settlement and 3 times (extended from 16:45 to 23.50) for the next-day settlement of the RUB/USD rate.

on NASDAQ, as the analysis indicates a decrease in liquidity. Fan and Lai (2006) investigate the effect of the extension of the trading hours on the intraday patterns on the Taiwan Stock Exchange and document a link between the extension of trading hours and transaction costs, but not volume or volatility. Using intraday data from the Tokyo Stock Exchange futures market, Miwa (2019) examines the overreaction phenomenon caused by extending trading hours and finds that extending trading hours has a negative impact on price efficiency, which is also documented by Lee et al. (2009) and Miwa and Ueda (2017). Moreover, many stock markets have introduced an opening or a closing session, leading to an extension of trading hours. However, these extensions are not relevant for the trading hours extension analyzed in the current study. This is because opening or closing sessions were implemented as separate sessions and have different auction systems.

The theoretical analysis of volatility in the forex market focuses on information asymmetry and overnight portfolio risk, which are seen as the sources of intraday volatility (Fan and Lai 2006). Owing to overnight portfolio risk, traders adjust their portfolios or take risk averse positions at the close and readjust their position when the market reopens; in other words, the portfolio considered optimal during the continuous trading period differs from that considered optimal during the non-trading period (Gerety and Mulherin 1992). Particularly, dealers on the forex markets adjust their prices to control their inventory (Lyons 1995).[4] Therefore, opening and closing times are expected to be more volatile.

French and Roll (1986) argue that there are three reasons the price volatility during the opening session is higher than the closing time of the market. First, public information is more likely to flow to the market when markets are open. Second, private information that causes volatility affects prices when used by informed traders. Finally, volatility due to mispricing is only possible when the market is open. According to French and Roll (1986), although a large part of volatility is caused by incorrect pricing, the main reason for volatility in asset prices is private information. This intraday volatility pattern is amplified by the fact that investors want to trade when the market is concentrated and deep because they can take advantage of their information more easily (Admati and Pfleiderer 1988). In summary, both the overnight risk and information asymmetry lead to higher volatility at the open and close of the market.

Additionally, numerous studies have investigated the intraday structure of volatility, spread, return and volume, paying only limited consideration to trading hours in forex markets. Sensoy and Serdengecti (2019) analyze how the type of counterparty and transaction affects the intraday volume-volatility relationship across various trading sessions around the world for US Dollar/Turkish Lira parity and conclude that only spot transactions of local clients have a positive, contemporary relationship with realized volatility. Furthermore, their study demonstrates that this relationship is valid only when global and local trading hours mostly overlap. Khademalomoom and Narayan (2019) examine the intraday patterns in the six most liquid currencies using hourly exchange rates.

[4] As Lyons (1995) points out the inventory effect is even stronger on the foreign exchange markets than on equity markets, since FX dealers—in contrast to equity traders—are mostly specialized in one currency and have less opportunity to hedge over several instruments.

They find that the exchange rates exhibit a strong presence of overlapping times effect. In another study related to time differences between markets, Pan et al. (2022) establish bidirectional return and volatility spillovers between Chinese and US stock markets. Zhang (2018) investigates intraday patterns in the exchange rates of 16 currencies against the USD using transaction data for the period 2010–2015. He claims that intraday patterns in forex returns exist in many countries. Krohn and Sushko (2022) document a high correlation between the bid-ask spreads in the forex swap and spot market. Using transaction data on the RUB/USD currency pair from the Moscow Interbank Currency Exchange during the period 2005–2014, Elaut et al. (2018) find a significant relationship between the first and last half-hour returns in the forex market. Additionally, many studies model the volatility in foreign exchange using intraday data (Andersen and Bollerslev 1998; Dunis et al. 2013; Frömmel et al. 2008; Gau 2005; Hattori 2020; Lyócsa et al. 2021; Qiu et al. 2019; Seemann et al. 2011; Su 2021) and daily data (Abdullah et al. 2017; Du and Hu 2012; Kočenda and Moravcová 2019; Viola et al. 2019).

Data and methodology

Data

We use the tick-by-tick transaction and quotes data for the next-day settlement of the RUB/USD (USD000UTSTOM or TOM) currency pair and same-day settlement of the RUB/USD (USD000000TOD or TOD) currency pair traded on the Moscow Exchange Foreign Exchange Market during the period 2005- 2013 to analyze the impact of the trading hours extension on volatility in forex markets. The data are comprised of transactions and quotes from three months prior to and three months following each extension of trading hours of both TOM and TOD.

Given that spot trading in the RUB/USD currency pair equals 1.66% of the total forex spot trading volume in 2013, the MOEX is the largest currency exchange in Russia and Eastern Europe and globally the 12th largest (Elaut et al. 2018). The data set provides two advantages: First, considerably deep data avoids a number of small sample problems that researchers often encounter in the microstructure literature.[5] Second, this study uses two different RUB/USD with different market segments and different trading extension dates.

The evolution of the TOM-RUB/USD and TOD-RUB/USD exchange rates over the period 2003–2013[6] is illustrated in Fig. 1.

Since 1999, the Bank of Russia (BoR) has regulated the exchange rate under a floating exchange rate regime. Starting in February 2009, the BoR set the operational band and progressively increased its width to ensure more flexibility. The width of the band was set at 7 Rubles from 07.24.2012 to 08.17.2014, and 9 Rubles starting on 08.18.2014 (BoR 2019). In our sample, three events occurred before January 2009 and three events took place after this date. Since the results for all of these are quite similar, we can conclude

[5] Kou et al. (2021a, b) utilised transactional data to improve the predictive power of bankruptcy prediction for SMEs.

[6] As one reviewer points out, a more recent sample period would be appreciated. This is not possible due to the lack of trading hours extensions afterwards. However, the trading mechanism and market structure stayed the same, so the results are representative. Furthermore, the period after 2013 was characterized by severe crises, such as the Crimea crisis 2014 and the current invasion in the Ukraine, which were both followed by Western sanctions on Russia affecting market volatility, and the COVID-19 pandemic.

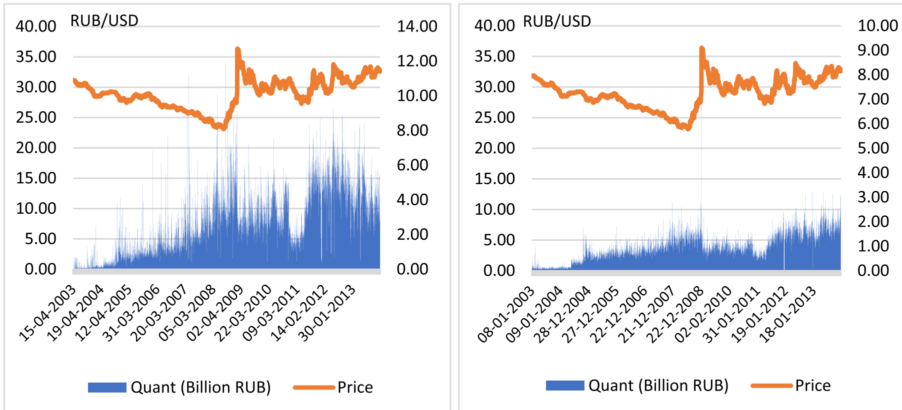

Fig. 1 Daily weighted average price and total quantity of TOM and TOD on MOEX

Table 1 Overview of trading sessions on MOEX exchange for RUB/USD

USD000UTSTOM RUB/USD				**USD000000TOD RUB/USD**			
Start Date	**End Date**	**Opening**	**Closing**	**Start Date**	**End Date**	**Opening**	**Closing**
–	31/08/2005	10:00	16:45	–	16/06/2005	10:00	13:30
01/09/2005	30/06/2011	10:00	17:00	20/06/2005	10/11/2008	10:00	14:00
01/07/2011	28/12/2012	10:00	19:00	11/11/2008	11/04/2013	10:00	15:00
08/01/2013	–	10:00	23.50	13/04/2013	–	10:00	17:15

that the effect of the BoR's widening the operational band does not harm our analyses and findings.

Operating since 1992, MOEX is Russia's oldest regulated market. In 2018, its operations accounted for approximately 68% of the USD/RUB and 78% of the EUR/RUB trading. The average daily trading volume of all instruments is 24.3 billion USD. The MOEX trading system provides a level playing field for all trading members and registered clients in entering and executing forex buy/sell orders and accessing market data. Orders are executed in the automated orders-matched system (Moex 2019).

MOEX extended trading hours three times for each session, TOM and TOD, during the period 2005–2013. The changes in the opening and closing times of trading sessions are presented in Table 1.

The RUB/USD currency pair trades as TOM and TOD contracts on MOEX. Both TOM and TOD currency pairs start trading at 10:00 a.m. (GMT + 3). The closing hour of TOM has been extended from 16:45 to 23.50 and that of TOD has been extended from 13:30 to 17:15. Given that the trading hour extension from 19:00 to 23:50 of TOM is a night session, it has been excluded from the analyses. Thus, we analyze two trading hours extensions of TOM and three of TOD.

Statistics of 5- and 15-min interval intraday returns, volume, and spread are summarized in Tables 2 and 3, respectively. The intraday regular returns and max–min returns are calculated using Eqs. (1) and (2). As expected, the max–min returns maintain higher values. The regular return is on average negative at the opening time (10:00–10:30) and positive at closing (final 30 min).

Table 2 Descriptive statistics of different measures of 5-min returns and volume of both TOD and TOM

	Period	Mean	Max	Min	SD
Regular return	Opening	− 0.0004	0.5448	− 0.5739	0.0418
	Midday	− 0.0001	0.3672	− 0.3368	0.0181
	Closing	0.0006	0.2150	− 0.1798	0.0198
	Overall	− 0.0001	0.5448	− 0.5739	0.0213
Max–min Return	Opening	0.0311	0.7048	0.0000	0.0526
	Midday	0.0187	0.6943	0.0000	0.0260
	Closing	0.0223	0.5043	0.0000	0.0298
	Overall	0.0201	0.7048	0.0000	0.0298
Volume (Millions)	Opening	36.34	699.00	0.0200	35.81
	Midday	24.21	1010.00	0.0010	27.32
	Closing	16.69	651.00	0.0040	24.64
	Overall	24.61	1010.00	0.0010	28.25
Bid-ask spread	Opening	0.0081	0.1296	0.0000053	0.0061
	Midday	0.0072	0.0575	0.0000017	0.0049
	Closing	0.0093	0.1262	0.0000810	0.0065
	Overall	0.0074	0.1291	0.0000017	0.0052

Methodology

To examine the effect of trading hours extension on volatility, returns used for calculating volatility are calculated using the formulas below. Returns are calculated separately for both 5- and 15-min intervals for TOM and TOD using the tick-by-tick transaction data. To analyze volatility, days are divided into three periods: 30 min starting from 10:00 a.m. (opening time), from 10:30 a.m. to 30 min before the closing time (midday), and the last 30 min (closing time). A total of two different measurements of return, given in the following equations, are utilized to analyze volatility for intraday level. In our sample,

Table 3 Descriptive statistics of different measures of 15-min returns and volume of both TOD and TOM

	Period	Mean	Max	Min	SD
Regular return	Opening	− 0.0001	0.6010	− 0.5423	0.0702
	Midday	0.0001	0.3514	− 0.4217	0.0285
	Closing	0.0028	0.1830	− 0.1874	0.0293
	Overall	0.0003	0.6010	− 0.5423	0.0342
Max–min return	Opening	0.0660	0.7048	0.0000	0.0860
	Midday	0.0376	0.7115	0.0000	0.0421
	Closing	0.0470	0.5155	0.0000	0.0460
	Overall	0.0409	0.7115	0.0000	0.0485
Volume (Millions)	Opening	109.00	1580.00	0.22	91.27
	Midday	72.00	1350.00	0.15	65.72
	Closing	49.91	736.00	0.73	56.62
	Overall	73.26	1580.00	0.15	68.73
Bid-ask spread	Opening	0.0090	0.1311	0.000051	0.0062
	Midday	0.0122	0.3216	0.000087	0.0191
	Closing	0.0078	0.2109	0.000003	0.0056
	Overall	0.0083	0.3216	0.000003	0.0077

there are five trading hour extension events. In each case, we used the data of the transaction book of MOEX utilizing windows that span over three months before and three months after each event and during the sample periods, Eqs. (1) and (2) are utilized to calculate the intraday return for 5- and 15-min intervals, respectively.

$$\text{Regular return (rr)} : rr_{i,t} = \log\left(P_{i,t}^{End} \middle/ P_{i,t}^{Beg}\right) * 100 \tag{1}$$

$$\text{Max} - \text{min return } (rmm) : rmm_{i,t} = \log\left(P_{i,t}^{Max} \middle/ P_{i,t}^{Min}\right) * 100 \tag{2}$$

The expressions $rr_{i,t}$ and $rmm_{i,t}$ represent different measures of the intraday returns on day t for intraday interval i. The variable $P_{i,t}^{End}$ represents the exchange rate on day t at the end of intraday interval i while $P_{i,t}^{Beg}$ is the exchange rate on day t at the beginning of intraday interval i. $P_{i,t}^{Max}$ represents the maximum exchange rate on day t in interval i, and $P_{i,t}^{Min}$ is the minimum exchange rate on day t in the intraday interval i.

Given that we examine the effects of trading hours extensions on volatility, diverse measures of historical volatility are used. These measures are given in Eqs. (3), (4), (5), and (6).

$$\hat{\sigma}_{hv} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(r_{i,t} - \bar{r})^2} \tag{3}$$

$$\hat{\sigma}_{PARK} = \sqrt{\left(\ln(P_{i,t}^{Max}/P_{i,t}^{Min}\right)^2 * 4\ln(2)} \tag{4}$$

$$\hat{\sigma}_{GK} = \sqrt{0.5 * \left(\ln(P_{i,t}^{Max}/P_{i,t}^{Min})\right)^2 - 0.39 * \left(\ln\left(P_{i,t}^{End}/P_{i,t}^{Beg}\right)\right)^2} \tag{5}$$

$$\hat{\sigma}_{RS} = \sqrt{\left(P_{i,t}^{Max} - P_{i,t}^{Beg}\right).\left(P_{i,t}^{Max} - P_{i,t}^{End}\right) + \left(P_{i,t}^{Min} - P_{i,t}^{Beg}\right).\left(P_{i,t}^{Min} - P_{i,t}^{End}\right)} \tag{6}$$

$\hat{\sigma}_{hv}$ stands for the classical standard deviation and N is the number of the observation (both 5- and 15-min returns) in opening, midday, and closing time in the period three months before and after the trading hours extensions, $\hat{\sigma}_{PARK}$ (*PARK*), $\hat{\sigma}_{GK}$ (*GK*), and $\hat{\sigma}_{RS}$ (*RS*) represent the various historical volatility measures proposed by Parkinson (1980), Garman and Klass (1980), and Rogers and Satchell (1991), respectively. In addition to $\hat{\sigma}_{hv}$, *PARK*, *GK*, and *RS* measures of the volatility were added to our analyses to derive robust results. According to Będowska-Sójka and Kliber (2021), $\hat{\sigma}_{GK}$ (*GK*) appears to be the widest measure of volatility.

Andersen et al. (2001a, b) and Andersen et al. (2001a, b) proposed realized volatility for intraday return in stock and foreign exchange markets. Following Taylor (1986), Schwert (1989), Andersen et al. (2003), Paye (2012), Sévi (2014), Wang et al. (2018), Sensoy and Serdengecti (2019), Zhang et al. (2021) and Ma and Tanizaki (2022), the squared intraday 5- and 15-min intraday returns are summed to construct a proxy for the volatility of RUB/USD exchange rate. For a given day t, the realized volatility is defined as:

$$RV_{j,t} = \sum_{j=1}^{Z} r_i^2, RV_t = \sum_{i=1}^{3} RV_{j,t} \tag{7}$$

where Z is the number of intraday periods at opening, midday, or closing in day t. For example, Z equals 6 at opening time when the intraday frequency is 5 min, as the first 30 min include six 5-min periods. Z equals 2 at the opening when the intraday frequency is 15 min, as the first 30 min include two 15-min periods. During the period 20.06.2005–02.09.2005, there are 36 or 12 5- or 15-min intraday intervals for TOD, respectively. Equation (7) gives daily realized volatility by summing realized volatility calculated for opening, midday, and closing times. Equations (1) and (2) calculate realized volatility for the various measures of return.

Andersen and Bollerslev (1997), Andersen et al. (2001a, b) and Andersen et al. (2003) argued that realized volatility given in Eq. (7) is less noisy and a better measure of the ex-post variance than the squared returns. On the other hand, such volatility is leptokurtic and errors are non-Gaussian. Therefore, statistical inference gathered from ordinary least squares (OLS) is faulty. To obtain Gaussian distribution, we follow Paye (2012), Wang et al. (2018) Qiu et al. (2019), and Dai et al. (2020) by calculating natural logarithms of realized volatility.[7]

$$V_t = \log\left(RV_t\right) \tag{8}$$

Paye (2012) and Wang et al. (2018) estimated realized volatility using the following equation, applying a lagged autoregressive model (AR) to examine the volatility of crude oil while Dai et al. (2020) examined RMB/USD exchange rate fluctuations. They used the AR process for up to six lags in addition to exogenous variables (X). Christoffersen (2012) also proposed a similar equation for forecasting realized variance using intraday data.

$$V_{t+1} = \omega + \sum_{i=0}^{p-1} \propto_i V_{t-i} + \beta X_t + \varepsilon_{i+1} \tag{9}$$

Paye (2012), Christoffersen (2012) and Wang et al. (2018) used Eq. (9) to examine the effects of trading hours extensions on exchange rate volatility. In addition, ARMA and GARCH models are used to calculate the estimates. The ARMA-GARCH model is the combination of ARMA and GARCH, proposed and developed by Engle (1982) and Bollerslev (1986), respectively. The realized volatility equation based on lagged values is also used in heterogeneous autoregression type models (Audrino and Knaus 2016; Corsi 2009; Corsi et al. 2008; Degiannakis and Livada 2016; Patton and Sheppard 2015; Qiu et al. 2019; Todorova and Souček 2014; Wang et al. 2016).

Ling and McAleer (2003) study the theoretical properties of the multivariate ARMA-GARCH model, which Nakatsuma and Tsurumi (1996), Li et al. (2002), and later Ghahramani and Thavaneswaran (2006), Wiphatthananthakul and Sriboonchitta (2010), Liu et al. (2011), Laurent et al. (2016), and Smolović et al. (2017) also used.

[7] The Jarque–Bera normality test is applied to residuals obtained from Eq. (10), and we found that residuals are normally distributed in the regressions where both rr and rmm are used in both 5-min and 15-mute intervals.

$$V_t = \omega + \sum_{i=1}^{p} \emptyset_i V_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t + \delta_1 DTHC_t + \delta_2 DUR_t$$
$$\varepsilon_t = \sigma_t z_t \tag{10}$$
$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=j}^{s} \beta_j \sigma_{t-j}^2$$

In Eq. (10), ω is a constant while $\emptyset_i$ is the ith autoregressive coefficient. The variable θ_j is the jth moving average coefficient, and ε_t represents the error term at time t. The variables p and q are the orders of autoregressive and moving average terms, respectively. The variable ε_t expresses changing variance over time and is equal to $\sigma_t z_t$, which is a white noise sequence with a mean of 0 and a variance of 1. Meanwhile, σ_t has an autoregressive conditional heteroskedastic process, which means that the current conditional variance depends on the previous conditional variance. To satisfy conditions of the conditional variance equation, the parameters, α_0, α_1,…,α_m, β_0, β_1,…,β_n must be equal to or greater than 0, and $\sum_{i=1}^{\max(m,s)} \left(\propto_i + \beta_j\right)$ must be less than 1 (Bollerslev 1986). The expression $DTHC_t$ functions as a dummy variable, which takes the value of 0 prior to and 1 following the extension of trading hours of TOD and TOM. The variable DUR_t represents the total minutes that the trading hours are extended.

As Li et al. (2022) mention, the distributions of financial data are inherently complex; to identify the factor behind the change in volatility, we calculated the probability of informed trading at opening time in MOEX following Yung (2005), Elaut et al. (2018), and Pöppe et al. (2016). The calculated probability of informed trading allows us to determine whether trading hours extension attracts informed traders or liquidity providers.

In the first step, since our data do not have information about the trade initiator, we applied the EMO (Ellis et al. 2000) trade classification rule, which is modified by Chakrabarty et al. (2007).

Maximizing the probability of correct selection is a widespread problem in many studies and real life (Kou et al. 2021a; b). In market microstructure studies, the correct selection of the buy-sell order has been investigated since late 1988. The trade-by-trade classification rules include the tick rule (TR) (Blume et al. 1989), the quote rule (QR) (Hasbrouck 1988), combinations of TR and QR, Lee and Ready rule (LR) (Lee and Ready 1991), EMO (Ellis et al. 2000), MEMO (Chakrabarty et al. 2007), and bulk volume classification (Easley et al. 2013, 2012). Although studies including Omrane and Welch (2016), Panayides et al. (2019), Savickas and Wilson (2003) and Lu and Wei (2009) tested the accuracy of these rules and found different levels, we follow Frömmel et al. (2020), who test trade classification rules for the RUB/USD from MOEX covering the period from mid-2011 to 2014 and found the best choice for classifying trades is MEMO.

In the second step, we calculate the dynamic probability of informed trading following Chang et al. (2014) and Elaut et al. (2018). To segregate the unexpected first 30-min return component (ε_t) from the return series while controlling for day-of-the-week effects and time-of-day-effects, we first estimated Eq. (11).

$$r_t = \propto_0 + \sum_{i=1}^{4} \propto_{1i} .D_i^{Day} + \sum_{j=1}^{J} \propto_{2j} .D_j^{int} + \sum_{k=1}^{K} \propto_{3k} .r_{t-k} + \varepsilon_t \quad (11)$$

where r_t is the return in the first 30 min, D_i^{Day} is the dummy variable for controlling for day-of-the-week effects, D_j^{int} represents the dummy variable for time-of-day-effects, and r_{t-k} is lagged half-hour returns lagged up to 18 intraday half-hour intervals.

A lack of autocorrelation patterns in unexpected returns, that is, contrarian trading, reveals the existence of informed trading (Chang et al. 2014). According to Avramov et al. (2006), informed trading occurs when sell trades in the existence of positive unexpected returns do not display any autocorrelation. Utilizing Chang et al.'s (2014) methodology, we calculate the probability of informed trading ($DPIN_t$) using the following formula:

$$DPIN_t = \frac{NB_t}{NT_t}(\varepsilon_t < 0) + \frac{NS_t}{NT_t}(\varepsilon_t > 0) \quad (12)$$

In Eq. (12), NB_t, NS_t, and NT_t represents the number of buy, sell, and total trades, respectively, made during the first 30-min interval from t_0 to t_1. ($\varepsilon_t < 0$) and ($\varepsilon_t > 0$) are indicator variables that determine the sign of the trades. ($\varepsilon_t < 0$) equals 1 when the unexpected return is negative and ($\varepsilon_t > 0$) equals 1 when the unexpected return is positive, in all other cases ($\varepsilon_t > 0$) and ($\varepsilon_t < 0$) is zero.

Results

This study utilizes various methodologies to examine the effect of an extension of trading hours on the volatility of the exchange rate of the Ruble versus the US Dollar. First, a graphic representation of the various historical volatility measures for 5- and 15-min intraday intervals serves as a starting point. Second, statistical comparisons are drawn between various historical volatility measures. To demonstrate the effect of trading hour extension on volume and spread, graphical and statistical comparisons are also given. Third, the ARMA-GARCH regression method is applied to variables derived from MOEX transaction data for the period 2005–2013. Finally, the probability of informed trading is calculated by applying the trade classification rule of modified EMO.

In the following figures, the volatility of the RUB/USD exchange rate of TOM and TOD three months before and three months after the trading hours extensions are compared (5-min intervals left, 15-min intervals right). The standard deviation of regular returns (*rr*) obtained from Eq. (1) as well as max–min (*rmm*) returns obtained from using Eq. (2) are displayed in Fig. 2. In the graphs, "Before" and "After" denote the values three months before and three months after the trading hour extension, respectively.

Trading hours extensions increase the volatility of the RUB/USD exchange rate as traded on MOEX. Independent from the sampling frequency and the volatility, we see the same picture. The volatility remarkably increased at opening time, whereas no systematic change is found for the other parts of the day (midday, closing), differences are small and direction switches. However, there is also a slight, but significant (see Table 4) increase in volatility during the day.

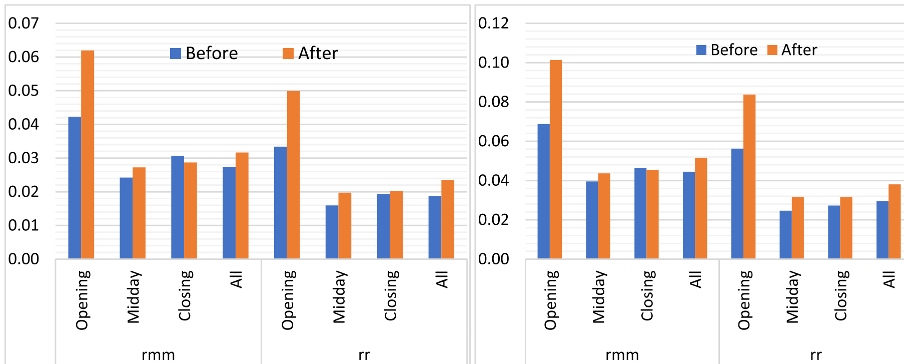

Fig. 2 Standard deviation of 5-min and 15-min returns

Table 4 Comparison of volatility measures, volume and spread for 5-min intervals

	B/A	Count	SD		Mean Volatility			Mean Volume (mln.)	Mean Spread
			rr	*rmm*	*Park*	*RS*	*GK*		
Opening	Before	2080	0.033	0.042	0.043	0.009	0.015	32.65	0.0077
	After	1769	0.050	0.062	0.062	0.014	0.021	40.68	0.0085
	F/t -Stat	Dif	0.45***	0.46***	6.67***	7.23***	6.71***	6.69***	4.02***
Midday	Before	17,183	0.016	0.024	0.026	0.006	0.009	21.25	0.0078
	After	19,702	0.020	0.027	0.036	0.009	0.013	26.80	0.0068
	F/t -Stat	Dif	0.66***	0.79***	21.61***	21.97***	21.16***	19.95***	− 15.75***
Closing	Before	2087	0.019	0.031	0.036	0.008	0.01	18.69	0.0104
	After	1747	0.020	0.029	0.038	0.009	0.013	14.29	0.083
	F/t -Stat	Dif	0.90**	1.14***	1.33	0.96	0.47	− 5.49***	− 10.59***
All Day	Before	21,350	0.019	0.027	0.029	0.006	0.010	22.11	0.0077
	After	23,218	0.023	0.032	0.038	0.009	0.013	26.92	0.0072
	F/t -Stat	Dif	0.64***	0.75***	19.81***	21.03***	19.51***	18.23***	− 9.75***

*** and ** indicates a 1% and 5% level of significance, respectively. The variance ratio test is used for variance comparisons of rr and rmm. The volatility measure of Park, RS and GK are tested using a classical t-test for mean difference with unequal variances. For the mean difference of volume and spread, the classical t-test is also used with unequal variances

Various volatility measures as proposed by Parkinson (1980), Garman and Klass (1980), and Rogers and Satchell (1991) defined in Eqs. (4), (5), and (6) respectively, are compared in Fig. 3, which confirm the results from Fig. 2.

According to Figs. 2 and 3, independent from how volatility is measured, trading hours extensions increase the volatility of exchange rates regarding 5- and 15-min intraday intervals. This is most pronounced for the market opening, less for the midday, whereas volatility before the closing rather and not for all measures significantly declines.

The average volume and spread comparing before and after the trading hour extensions are illustrated in Figs. 4 and 5, respectively.

As seen in Fig. 4, trading volume follows volatility. While the highest increase in volume is observed at opening time, the volume slightly decreased at closing time. Based on graphical illustrations, after the trading hour extension, volume shifts from closing to morning. On the other hand (see Fig. 5),while the spread increases at opening time, it decreases at midday and closing time (in the 5-min interval), indicating higher liquidity.

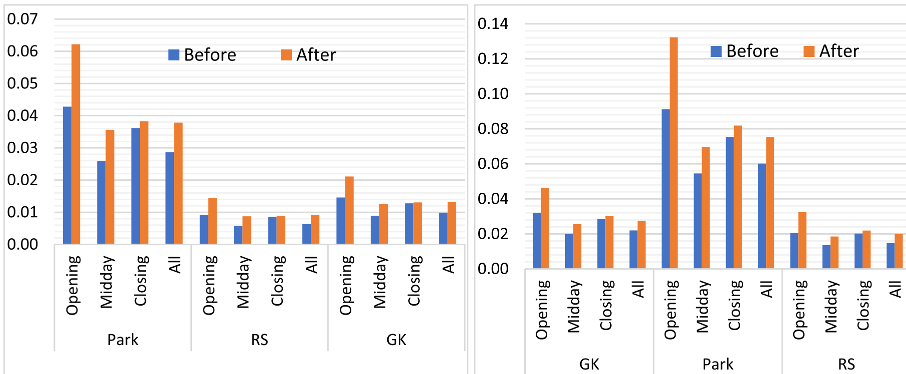

Fig. 3 Park, RS and GK measurements of volatility for 5- and 15-min intervals

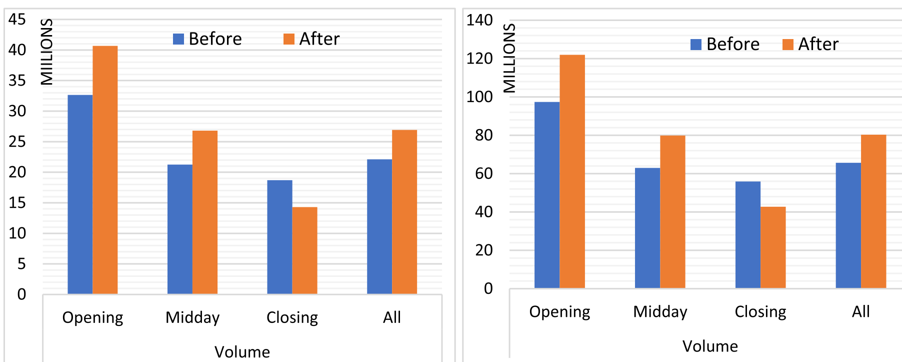

Fig. 4 Average volume for 5 and 15-min intervals

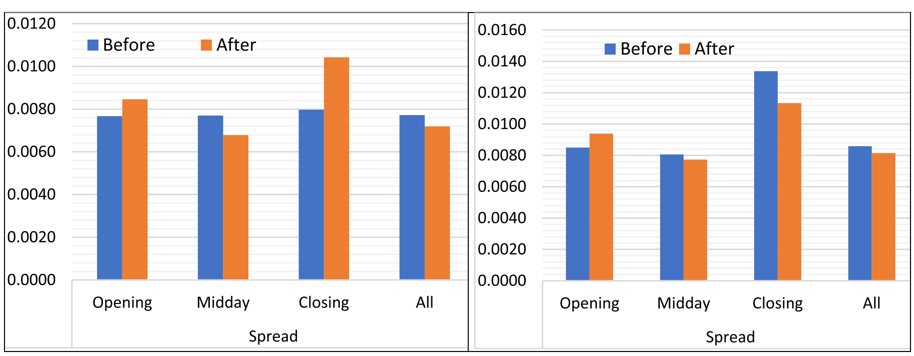

Fig. 5 Average spread for 5- and 15-min intervals

The significance levels for 5- and 15-min intraday intervals are provided in Tables 4 and 5, respectively. Various measures of historical volatility, volume, and spread are compared based on standard deviation and mean values, which are calculated before and after the trading hour extension in MOEX. They support the insights from Figs. 2, 3 and 4.

The trading hour extensions lead to an increase in volume and volatility in the market as a whole. Although volume and volatility increased significantly at the opening

Table 5 Variance comparison of volatility measures, volume and spread for 15-min intervals

	B/A	Count	SD		Mean Volatility			Mean Volume (Millions)	Mean Spread
			rr	*rmm*	*Park*	*RS*	*GK*		
Opening	Before	700	0.056	0.069	0.091	0.021	0.032	97.35	0.0085
	After	590	0.084	0.101	0.132	0.032	0.046	122.00	0.0094
	F/t -Stat	Dif	0.45***	0.46***	5.03***	5.53***	5.04***	4.60***	2.72***
Midday	Before	5803	0.025	0.040	0.055	0.014	0.020	63.00	0.0080
	After	6608	0.031	0.044	0.070	0.019	0.026	79.90	0.0077
	F/t -Stat	Dif	0.61***	0.82***	12.16***	12.47***	11.55***	14.73***	− 2.99***
Closing	Before	697	0.027	0.046	0.075	0.021	0.029	55.92	0.013
	After	583	0.031	0.045	0.082	0.022	0.030	42.74	0.011
	F/t -Stat	Dif	0.75***	1.05	1.52	1.22	0.93	− 14.19***	− 1.63*
All Day	Before	7200	0.029	0.044	0.060	0.015	0.022	65.65	0.0085
	After	7781	0.038	0.051	0.075	0.020	0.028	80.30	0.0081
	F/t-Stat	Dif	0.60***	0.75***	11.65***	12.45***	11.17***	13.28***	− 2.96***

*** and ** indicates a 1% and 5% level of significance, respectively. The variance ratio test is used for variance comparisons of rr and rmm. Volatility measures of Park, RS and GK are tested using a classical t-test for mean difference with unequal variances. For the mean difference of volume and spread, the classical t-test is also used with unequal variances

Table 6 Results of unit-root tests for logarithmic realized volatility

	5-min intraday intervals		15-min intraday intervals	
	ADF test stat	PP test stat	ADF test stat	PP test stat
$Log(RV_{rr})$	− 3.70***	− 21.06***	− 3.50***	− 16.60***
$Log(RV_{rmm})$	− 6.61***	− 17.83***	− 3.57***	− 18.22***

*** indicates a 1% significance level

and midday time, volume significantly decreased at closing time and the change is not significant. Considering the increase in volume and volatility during the whole day and as well as the increase at opening and midday time, a positive volume and volatility relationship supports previous findings (Andersen 1996; Bauwens et al. 2006; Clark 1973; Koubaa and Slim 2019; Lamoureux and Lastrapes 1990; Sensoy and Serdengecti 2019; Tauchen et al. 1996).

Equation (10) is utilized to examine the effect of trading hours extension on volatility using a more sophisticated methodology. The stationarity of the variables must be tested to obtain non-spurious regression results and correct R^2 values.

The results of the unit-root tests applied to the variables are reported in Table 6. The stationarity of the variables is confirmed by the Augmented Dickey-Fuller-Fisher Chi-Square (Dickey and Fuller 1979) and Phillips-Perron-Fisher Chi-Square (Phillips and Perron 1988) tests. In Table 6, RV_{rr} shows realized volatility of regular return where the regular return was obtained using Eq. (1) and realized volatility obtained using Eq. (7). Similarly, RV_{rmm} represents realized volatility of max–min return where the latter is acquired using Eq. (2) and realized volatility acquired using Eq. (7).

Estimating Eq. (10), we then apply the ARMA-GARCH methodology to a pooled sample of TOM and TOD exchange rates of RUB/USD to determine the impact

Table 7 ARMA-GARCH estimation of realised volatility for 5- and 15-min intervals

Variable	5-min intraday intervals				15-min intraday intervals			
	Regular return—rr (A)		Maxmin Return—rmm (B)		Regular return -rr (C)		Maxmin Return -rmm (D)	
	Coef	z-stat	Coef	z-stat	Coef	z-stat	Coef	z-stat
C	− 5.200	− 16.66***	− 4.190	− 13.35***	− 5.583	− 23.92***	− 4.192	− 14.42***
DTHC	0.587	3.42***	0.555	3.44***	0.517	2.49**	0.599	3.62***
DUR	0.014	3.43***	0.015	3.97***	0.015	5.01***	0.014	3.96***
AR(1)	0.255	6.27***	0.267	6.25***	0.351	9.45***	0.253	6.73***
AR(2)	0.142	3.60***	0.124	3.25***	0.235	5.87***	0.114	2.76***
AR(3)	0.640	8.13***	0.637	7.89***	–	–	0.076	1.94*
AR(4)	− 0.116	− 2.16**	− 0.091	− 1.59	0.116	3.04***	0.456	6.92***
MA(3)	− 0.574	− 6.44***	− 0.587	− 6.76***	0.133	3.08***	–	–
MA(4)	–	–	–	–	–	–	− 0.400	− 5.95***
Variance Equation								
C	0.013	2.10**	0.018	2.22**	0.005	1.61	0.020	1.80*
RESID(-1)^2	0.083	3.85***	0.109	3.97***	0.015	1.67*	0.088	3.17***
GARCH(-1)	0.905	42.13***	0.873	32.05***	0.976	104.56***	0.889	28.68***
T-DIST. DOF	–	–	–	–	10.653	2.39**	10.970	2.14**
Adj. R^2	0.4141		0.4363		0.5238		0.4561	
ARCH-LM Stat	0.1185		0.2368		0.1136		0.1001	

***, ** and * indicate 1%, 5% and 10% levels of significance, respectively. Correlogram Q-statistics show that no autocorrelation is present in the ARMA-GARCH regression. Although the coefficient of DTHC and DUR have positive directions and the same significance level in OLS regression, the serial correlation LM tests and ARCH LM tests verify that OLS estimates indicate autocorrelation and heteroscedasticity problems. ARMA-GARCH estimations past the ARCH LM test state that there is no heteroscedasticity. According to the Jarque–Bera test, the residual of the ARMA-GARCH estimations is normally distributed

of trading hours extensions on realized volatility. Calculations using Eq. (10) are repeated for both 5- and 15-min intraday intervals as well as two different measures of return, which are used to calculate realized volatility during the period 2005–2013.

Columns (A), (B), (C), and (D) of Table 7 display the ARMA-GARCH estimates from Eq. (10). Daily realized volatility is derived from the two different measures of returns using Eqs. (1) and (2), respectively.

As seen in Table 7, four different estimates based on 5- and 15-min intraday intervals as well as two different measures of realized volatility (regular returns and max–min returns) are valid, as the coefficients of the RESID(-1)^2 and GARCH(-1) are significant at the 1% level and provide a fairly high adjusted R^2. In all equations, the required condition of GARCH estimation is satisfied. The AR process used up to four lags, as Paye (2012), Wang et al. (2018), and Dai et al. (2020) used the AR process with up to six lags. Panel (A) presents a 4-lag AR process and a MA(3) process. Panels (A) and (B) lists the coefficient AR processes up to three lags and an MA(3) with significance at the 1% level. The AR(4) process in Panel (A) is significant at the 5% level, but not significant in Panel (B). In Panels (C) and (D), the AR(1) and AR(2) processes are significant at the 1% level. To obtain the best fit and pass residual tests, an additional AR(4) process is used without AR(3) in Panel (C). Although MA(3) process is relevant in Panel (C), MA(4) process is used in Panel (D).

The results in Table 7 lead to the conclusion that realized volatility highly depends on the lags in the ARMA-GARCH process. Up to AR(2), the coefficient of the AR processes is significant at the 1% level with positive signs in all estimates. On the other hand, the coefficients of MA processes have negative signs with a 1% significance level.

The dummy variable *DTHC*, indicating the difference in realized volatility before and after the trading hours extensions in both TOD and TOM of the RUB/USD exchange rate, is used to investigate the effect of the trading hours extension on realized volatility. The coefficient of *DTHC* in Panel (A), in which realized volatility is derived from 5-min intraday intervals on regular returns, is positively significant at the 1% level. The result in Panel (B), in which daily realized volatility is derived from 5-min interval max–min returns, is similar to that in Panel (A) in terms of significance level and sign. Therefore, realized volatility measured in 5-min intraday intervals is different. Trading hours extensions are found to cause an increase in realized volatility in both max–min and regular return-based measurements. The coefficient of *DTHC* in Panel (D), in which realized volatility is derived from 15-min intraday intervals on max–min returns, is significant at the 1% level and has a positive sign as in Panels (A) and (B). The daily realized volatility derived from 15-min interval regular returns has a positive coefficient, significant at the 5% level. As a result, the realized volatility of TOD and TOM of the RUB/USD exchange rate prior to trading hours extensions is lower than that after trading hours extensions, which confirms the results from the previous analysis.

The effect of the duration of trading hours extensions on realized volatility in terms of minutes is illustrated in Table 7. As reported in Table 5, the coefficient of *DUR* is positive and significant at the 1% level in both realized volatilities derived from max–min and regular returns in both 5- and 15-min intraday intervals. The greater the length of the extension, the higher the realized volatility as a significant, positive correlation exists between *V* and *DUR.* This finding regarding the time length of the trading extension and realized volatility strongly supports the positive relationship between trading hours extensions and realized volatility.

The findings indicate that although trading hours extensions raise opportunities for more transactions and liquidity in forex markets, they also lead to higher volatility in the RUB/USD market. Furthermore, this distortion is more significant at opening and midday. The results are consistent with the findings of Lee et al. (2009), Miwa and Ueda (2017) and Miwa (2019), who also documented the negative impacts of trading hours extensions on price efficiency in stock markets.

The result of increased volatility mostly at the opening seems to be counterintuitive at first sight since the overnight gap has become smaller. Furthermore, it cannot be explained by an increased overlap with trading hours of stock exchanges all over the world, since this happens in the afternoon, not during the opening session that remained unchanged. A potential explanation is that the extension attracts informed traders rather than liquidity providers. As French and Roll (1986) revealed, informed traders are the main source of volatility when the market is open. While the latter rather lowers volatility (Hagströmer and Nordén 2013), informed trading rather increases volatility. We therefore hypothesize that after the trading hours extension, informed trading during the opening session has increased.

Table 8 The dynamic probability of informed trading for trading hour extension events

	Extension 1 (TOD)		Extension 2 (TOM)		Extension 3 (TOD)		Extension 4 (TOM		Extension 5 (TOD)	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
$NB_t\ (\varepsilon_t < 0)$	2696	4080	724	675	6891	1515	5752	8884	11,370	13,350
$NS_t(\varepsilon_t > 0)$	3940	2994	849	763	4544	992	5860	9219	12,050	18,761
NT_t	14,500	15,294	3554	3445	24,707	4987	24,663	39,244	48,893	66,830
$DPIN_t$	0.458	0.463	0.443	0.417	0.463	0.503	0.471	0.461	0.479	0.480
$\Delta DPIN_t$	+	–	+	–	+					

TOD is the RUB/USD rate for same day settlement, TOM is the RUB/USD rate for next day settlement

Table 9 The summary results of analyses for the different periods of the trading session

	All Day		Opening		Midday		Closing	
	5-min	**15-min**	**5-min**	**15-min**	**5-min**	**15-min**	**5-min**	**15-min**
Volatility	++++++[a]	++++++[a]	+++++	+++++	+++++	+++++	+	–
Volume	+	+	+	+	+	+	−	−
Spread	−	−	+	+	−	−	−	−

"+" denotes an increase "−" shows a decrease comparing before and after the trading extension. Since we measured volatility in 5 different ways, each sign indicates a measure of volatility. "a" denotes a sign for ARMA-GARCH estimation

To test our hypothesis we calculate the dynamic probability of informed trading (DPIN) (Chang et al. 2014) at the opening. The DPIN estimates before and after the trading hours extensions are reported in Table 8. Interestingly DPIN for the RUB/USD rate for same-day settlement increased at the opening time after the trading hour extension in MOEX. On the other hand, $DPIN_t$ for the RUB/USD rate for next-day settlement decreased.

Since informed traders request immediacy, the results are not surprising. Trading hour extensions increase the overlap of trading hours of MOEX with EU and US markets. Thus, the information flow increases during the overlapping trading time, which causes an increase in information flow in the market. Higher information leads to a decrease in the possibility of higher profit for informed traders. As Kyle (1985) stated, insider traders use their informational monopoly power to get profit from trading. Therefore, the informed traders shifted their volume from closing to opening time at which they have more power to utilize their information. On the other hand, since the information continuously flows to the market, their informational powers are limited. Therefore, they prefer to trade in same-day settlement RUB/USD rate. This type of behavioral change in informed traders leads to increase volume and volatility at the opening time of the MOEX.

The results of trading hour extension in MOEX are summarized in Table 9:

As seen from Table 9, the trading hour extension caused an increase in volatility and volume and a decrease in the spread in all day and midday time. At opening time, volatility, volume and spread increased simultaneously. At closing, the change in volatility is not significant, but spread and volume decreased.

Conclusion

The volatility of the exchange rate is one of the main issues that central banks or monetary regulators try to maintain at a minimum level. To do so, many regulatory measures, including changes in market microstructure, are put into force to stabilize or globally integrate the market. One such microstructure initiative may be altering or extending the trading hours of forex markets. This study examined the effect of trading hours extensions on forex rate volatility.

The effect of trading hours extensions on forex rates is analyzed using transaction data of the same- and next-day settlement of the RUB/USD currency pair traded on MOEX. The MOEX extended trading hours three times for the same-day and two times for the next-day settlement of the RUB/USD exchange rate during the period 2005–2013. The analyses are performed using various measures of historical volatility and daily realized volatility for 5- and 15-min intervals. ARMA-GARCH methodology is used to estimate realized volatility. To determine the factor that caused a change in volatility, the probability of informed trading is calculated by applying the trade classification rule of modified EMO to our data.

The extension of trading hours in the forex market is found to lead to a significant increase in historical volatility of the RUB/USD exchange rate in both 5- and 15-min intraday levels. The increment caused by the extension of trading hours is higher at opening than closing. The ARMA-GARCH results of realized volatility also demonstrate that the volatility of the RUB/USD exchange rate increased significantly after the extension of trading hours. Furthermore, the duration of the trading hours extension is found to have a significant effect on realized volatility, as a significant, positive relationship exists between realized volatility and the duration. Our findings are valid for both 5- and 15-min intraday levels as well as volatility measures based on both regular and max–min returns. Additionally, the trading hour extension caused an increase in volume and a decrease in the spread all day and at midday time. On the other hand, volume and spread increased at opening time.

While the trading hour extension causes less overnight information delayed to the morning, it also results in higher volatility, which supports the theory of information asymmetry. Taking the results on volume, spread, and probability of informed trading into consideration, we concluded that informed trading volume shifted from closing to opening time owing to more overlapping trading hours of the Russian market with the EU and US markets. More trading hours overlapping leads to a higher degree of information flow, which weakens the informational power of informed traders. As a result, informed traders shifted their volume from closing to opening time, at which they have more power to utilize their information, thus higher volatility and volume occurred during the opening session. Additionally, an increase in the spread at an opening time fits with the picture that trading hour extensions increase volume, but rather attract informed traders than increase liquidity.

Our results have theoretical, practical, and regulatory implications. From a theoretical viewpoint, to the best of our knowledge, this is the first study on the forex market. Although forex trading is formally open 24/7 and is performed simultaneously around the world, regional currency exchanges account for a large fraction of trading volume and price discovery typically occurs while they are open. Our results imply that an extension of trading hours does not necessarily reduce the overnight exposure and brings down volatility in the opening session. Although the overnight risk should decrease due to the smaller night gap with (limited) trading, traders face an even higher volatility during the opening session. Our results therefore corroborate those from equity markets (see e.g., Miwa 2019), despite the very different market structure. From a practical viewpoint, this means traders bear a higher risk of trading with informed traders, and particularly during the opening session (together with higher spreads), but in the day and closing session they can benefit from lower transaction costs.

The results also have implications for regulators and market operators. We conclude that regulatory authorities should consider the position of uninformed traders when trading hours extensions occur. Trading hours extensions may not necessarily add liquidity to the market, from which uninformed traders can benefit. On the other hand, overlapping the local market with international markets increases the information flows across markets and price discovery. Market operators may rather focus on the increased overall trading volume, which benefits them.

Future studies can further extend the insights from our research by the use of more detailed data sets. While trade classifications work reasonably well, using full details of the order and trading book helps to further increase the accuracy. More detailed data on the identity of traders will help to clarify the unrevealed role of trader groups on the market. Finally, using data from simultaneous trading on different markets will help investigate the effect of overlapping trading hours. However, since trading hours extensions only occur occasionally, opportunities will be rare.

Abbreviations

MOEX	Moscow Exchange Foreign Exchange Market
ARMA	Autoregressive moving average
GARCH	Autoregressive conditional heteroscedasticity
EMO	Ellis, Michaely and O'Hara, 2000
RUB	Russian Ruble
USD	US Dollar
TOD	The currency pair and same-day settlement of the RUB/USD
TOM	The currency pair and next-day settlement of the RUB/USD
BoR	Bank of Russia

Acknowledgements
Not applicable.

Author contributions
EK helped to conceive and design the study and analysis and drafted the manuscript. MF helped to conceive and design the study, conducted the data collection, and coordinated the research activities. All authors read and approved the final manuscript.

Funding
Not applicable.

Availability of data and materials
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

Received: 3 February 2022 Accepted: 25 April 2023
Published online: 21 July 2023

References

Abdullah SM, Siddiqua S, Siddiquee MSH, Hossain N (2017) Modeling and forecasting exchange rate volatility in Bangladesh using Garch models: a comparison based on normal and student's T-error distribution. Financ Innov 3(1):18. https://doi.org/10.1186/s40854-017-0071-z

Admati AR, Pfleiderer P (1988) A theory of intraday patterns: volume and price variability. Rev Financ Stud 1(1):3–40. https://doi.org/10.1093/rfs/1.1.3

Agarwalla SK, Jacob J, Pandey A (2015) Impact of the introduction of call auction on price discovery: evidence from the Indian stock market using high-frequency data. Int Rev Financ Anal 39:167–178. https://doi.org/10.1016/j.irfa.2015.01.012

Andersen TG (1996) Return volatility and trading volume: an information flow interpretation of stochastic volatility. J Financ 51(1):169–204. https://doi.org/10.1111/j.1540-6261.1996.tb05206.x

Andersen TG, Bollerslev T (1997) Heterogeneous information arrivals and return volatility dynamics: uncovering the long-run in high frequency returns. J Financ 52(3):975–1005. https://doi.org/10.1111/j.1540-6261.1997.tb02722.x

Andersen TG, Bollerslev T (1998) Deutsche mark-dollar volatility: intraday activity patterns, macroeconomic announcements, and longer run dependencies. J Financ 53(1):219–265. https://doi.org/10.1111/0022-1082.85732

Andersen TG, Bollerslev T, Diebold FX, Ebens H (2001a) The distribution of realized stock return volatility. J Financ Econ 61(1):43–76. https://doi.org/10.1016/S0304-405X(01)00055-1

Andersen TG, Bollerslev T, Diebold FX, Labys P (2001b) The distribution of realized exchange rate volatility. J Am Stat Assoc 96(453):42–55. https://doi.org/10.1198/016214501750332965

Andersen TG, Bollerslev T, Diebold FX, Labys P (2003) Modeling and forecasting realized volatility. Econometrica 71(2):579–625. https://doi.org/10.1111/1468-0262.00418

Audrino F, Knaus SD (2016) Lassoing the har model: a model selection perspective on realized volatility dynamics. Economet Rev 35(8–10):1485–1521. https://doi.org/10.1080/07474938.2015.1092801

Avramov D, Chordia T, Goyal A (2006) The impact of trades on daily volatility. Rev Financ Stud 19(4):1241–1277. https://doi.org/10.1093/rfs/hhj027

Barclay MJ, Hendershott T (2003) Price discovery and trading after hours. Rev Financ Stud 16(4):1041–1073. https://doi.org/10.1093/rfs/hhg030

Bauwens L, Rime D, Sucarrat G (2006) Exchange rate volatility and the mixture of distribution hypothesis. Empir Econ 30(4):889–911. https://doi.org/10.1007/s00181-005-0005-x

Będowska-Sójka B, Kliber A (2021) Information content of liquidity and volatility measures. Phys A Stat Mech Appl 563:125436. https://doi.org/10.1016/j.physa.2020.125436

Biais B, Glosten L, Spatt C (2005) Market microstructure: a survey of microfoundations, empirical results, and policy implications. J Financ Mark 8(2):217–264. https://doi.org/10.1016/j.finmar.2004.11.001

Blume ME, Mackinlay AC, Terker B (1989) Order imbalances and stock price movements on october 19 and 20, 1987. J Financ 44(4):827–848. https://doi.org/10.1111/j.1540-6261.1989.tb02626.x

Bollerslev T (1986) Generalized autoregressive conditional heteroskedasticity. J Econom 31(3):307–327. https://doi.org/10.1016/0304-4076(86)90063-1

BoR (2019) The History of the Bank of Russia FX Policy. Retrieved 20.12.2019 http://www.cbr.ru/eng/dkp/about_inflation/history/#:~:text=Since%201999%2C%20the%20Bank%20of,Russian%20economy%20as%20a%20whole

Chakrabarty B, Li B, Nguyen V, Van Ness RA (2007) Trade classification algorithms for electronic communications network trades. J Bank Finance 31(12):3806–3821. https://doi.org/10.1016/j.jbankfin.2007.03.003

Chang SS, Chang LV, Wang FA (2014) A dynamic intraday measure of the probability of informed trading and firm-specific return variation. J Empir Financ 29:80–94. https://doi.org/10.1016/j.jempfin.2014.02.003

Christoffersen PF (2012) 5: volatility modeling using intraday data. In: Christoffersen PF (ed) Elements of financial risk management, 2nd edn. Academic Press, San Diego, pp 93–120

Clark PK (1973) A subordinated stochastic process model with finite variance for speculative prices. Econometrica 41(1):135–155. https://doi.org/10.2307/1913889

Corsi F (2009) A simple approximate long-memory model of realized volatility. J Financ Economet 7(2):174–196. https://doi.org/10.1093/jjfinec/nbp001

Corsi F, Mittnik S, Pigorsch C, Pigorsch U (2008) The volatility of realized volatility. Economet Rev 27(1–3):46–78. https://doi.org/10.1080/07474930701853616

Dai Z, Zhu H, Dong X (2020) Forecasting Chinese industry return volatilities with rmb/usd exchange rate. Phys A Stat Mech Appl 539:122994. https://doi.org/10.1016/j.physa.2019.122994

Degiannakis S, Livada A (2016) Evaluation of realized volatility predictions from models with Leptokurtically and asymmetrically distributed forecast errors. J Appl Stat 43(5):871–892. https://doi.org/10.1080/02664763.2015.1079306

Dickey DA, Fuller WA (1979) Distribution of the estimators for autoregressive time series with a unit root. J Am Stat Assoc 74(366):427–431. https://doi.org/10.2307/2286348

Du D, Hu O (2012) Foreign exchange volatility and stock returns. J Int Finan Markets Inst Money 22(5):1202–1216. https://doi.org/10.1016/j.intfin.2012.07.001

Dunis C, Kellard NM, Snaith S (2013) Forecasting Eur-Usd implied volatility: the case of intraday data. J Bank Finance 37(12):4943–4957. https://doi.org/10.1016/j.jbankfin.2013.08.028

Easley D, Lopez de Prado M, O'Hara M (2013) Bulk classification of trading activity. Johnson School Res Pap Ser 8(6):14

Easley D, López De Prado MM, O'Hara M (2012) Flow toxicity and liquidity in a high-frequency world. Rev Financ Stud 25(5):1457–1493. https://doi.org/10.1093/rfs/hhs053
Elaut G, Frömmel M, Lampaert K (2018) Intraday momentum in FX markets: disentangling informed trading from liquidity provision. J Financ Mark 37:35–51. https://doi.org/10.1016/j.finmar.2016.09.002
Ellis K, Michaely R, O'Hara M (2000) The accuracy of trade classification rules: evidence from Nasdaq. J Financ Quant Anal 35(4):529. https://doi.org/10.2307/2676254
Engle RF (1982) Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econom J Econom Soc 50(4):987–1007. https://doi.org/10.2307/1912773
Fan Y-J, Lai H-N (2006) The intraday effect and the extension of trading hours for Taiwanese securities. Int Rev Financ Anal 15(4):328–347. https://doi.org/10.1016/j.irfa.2006.02.005
French KR, Roll R (1986) Stock return variances. J Financ Econ 17(1):5–26. https://doi.org/10.1016/0304-405x(86)90004-8
Frömmel M, D'Hoore D, Lampaert K (2020) The accuracy of trade classification systems on the foreign exchange market: evidence from the Rub/Usd market. Finance Res Lett. https://doi.org/10.1016/j.frl.2020.101892
Frömmel M, Mende A, Menkhoff L (2008) Order flows, news, and exchange rate volatility. J Int Money Financ 27(6):994–1012. https://doi.org/10.1016/j.jimonfin.2007.07.002
Garman MB, Klass MJ (1980) On the estimation of security price volatilities from historical data. J Bus 53(1):67–78. https://doi.org/10.1086/296072
Gau Y-F (2005) Intraday volatility in the Taipei FX Market. Pac Basin Financ J 13(4):471–487. https://doi.org/10.1016/j.pacfin.2004.12.002
Gerety MS, Mulherin JH (1992) Trading halts and market activity: an analysis of volume at the open and the close. J Financ 47(5):1765–1784
Ghahramani M, Thavaneswaran A (2006) Financial applications of Arma models with Garch errors. J Risk Finance 7(5):525–543. https://doi.org/10.1108/15265940610712678
Hagströmer B, Nordén L (2013) The diversity of high-frequency traders. J Financ Mark 16(4):741–770
Hasbrouck J (1988) Trades, quotes, inventories, and information. J Financ Econ 22(2):229–252
Hattori T (2020) A forecast comparison of volatility models using realized volatility: evidence from the bitcoin market. Appl Econ Lett 27(7):591–595. https://doi.org/10.1080/13504851.2019.1644421
Houston JF, Ryngaert MD (1992) The links between trading time and market volatility. J Financ Res 15(2):91–100. https://doi.org/10.1111/j.1475-6803.1992.tb00790.x
Hsieh T-Y, Lin C-C, Shiu Y-M (2011) Impact of tick-size reduction on intraday patterns of market quality: evidence from the Taiwan stock exchange. Asia Pac Manag Rev 16(2):105–118
Inci AC, Ozenbas D (2017) Intraday volatility and the implementation of a closing call auction at Borsa Istanbul. Emerg Mark Rev 33:79–89. https://doi.org/10.1016/j.ememar.2017.09.002
Kadioglu E (2021) Intraday analysis of regulation change in microstructure: evidence from an emerging market. Int J Emerg Mark. https://doi.org/10.1108/IJOEM-11-2020-1310
Khademalomoom S, Narayan PK (2019) Intraday effects of the currency market. J Int Finan Markets Inst Money 58:65–77. https://doi.org/10.1016/j.intfin.2018.09.008
King MR, Osler C, Rime D (2012) Foreign exchange market structure, players, and evolution. In: Handbook of exchange rates, pp 1–44
Kočenda E, Moravcová M (2019) Exchange Rate Comovements, Hedging and Volatility Spillovers on New Eu Forex Markets. J Int Finan Markets Inst Money 58:42–64. https://doi.org/10.1016/j.intfin.2018.09.009
Kou G, Xiao H, Cao M, Lee LH (2021a) Optimal computing budget allocation for the vector evaluated genetic algorithm in multi-objective simulation optimization. Automatica 129:109599. https://doi.org/10.1016/j.automatica.2021.109599
Kou G, Xu Y, Peng Y, Shen F, Chen Y, Chang K, Kou S (2021b) Bankruptcy prediction for SMEs using transactional data and two-stage multiobjective feature selection. Decis Supp Syst 140:113429. https://doi.org/10.1016/j.dss.2020.113429
Koubaa Y, Slim S (2019) The relationship between trading activity and stock market volatility: Does the volume threshold matter? Econ Model 82:168–184. https://doi.org/10.1016/j.econmod.2019.01.003
Krohn I, Sushko V (2022) FX spot and swap market liquidity spillovers. J Int Money Finance 120:102476. https://doi.org/10.1016/j.jimonfin.2021.102476
Kyle AS (1985) Continuous auctions and insider trading. Econometrica 53(6):1315–1335. https://doi.org/10.2307/1913210
Lamoureux CG, Lastrapes WD (1990) Heteroskedasticity in stock return data: volume versus garch effects. J Financ 45(1):221–229. https://doi.org/10.1111/j.1540-6261.1990.tb05088.x
Laurent S, Lecourt C, Palm FC (2016) Testing for jumps in conditionally Gaussian ARMA–GARCH models, a robust approach. Comput Stat Data Anal 100:383–400. https://doi.org/10.1016/j.csda.2014.05.015
Lee CMC, Ready MJ (1991) Inferring trade direction from intraday data. J Financ 46(2):733–746. https://doi.org/10.1111/j.1540-6261.1991.tb02683.x
Lee H-C, Chien C-Y, Chen H-L, Huang Y-S (2009) The extended opening session of the futures market and stock price behavior: evidence from the taiwan stock exchange. Rev Pac Basin Financ Mark Policies 12(03):403–416. https://doi.org/10.1142/S021909150900168X
Li T, Kou G, Peng Y, Philip SY (2022) An integrated cluster detection, optimization, and interpretation approach for financial data. IEEE Trans Cybern 52(12):13848–13861
Li WK, Ling S, McAleer M (2002) Recent theoretical results for time series models with Garch errors. J Econ Surv 16(3):245–269. https://doi.org/10.1111/1467-6419.00169
Ling S, McAleer M (2003) Asymptotic theory for a vector ARMA-GARCH model. Economet Theor 19(2):280–310. https://doi.org/10.1017/S0266466603192092
Liu H, Erdem E, Shi J (2011) Comprehensive evaluation of Arma–Garch(-M) approaches for modeling the mean and volatility of wind speed. Appl Energy 88(3):724–732. https://doi.org/10.1016/j.apenergy.2010.09.028

Lu YC, Wei YC (2009) Classification of trade direction for an equity market with price limit and order match: evidence from the taiwan stock market. Investm Manag Financ Innov 6(3):135–147
Lyócsa Š, Plíhal T, Výrost T (2021) FX market volatility modelling: Can we use low-frequency data? Finance Res Lett 40:101776. https://doi.org/10.1016/j.frl.2020.101776
Lyons RK (1995) Tests of microstructural hypotheses in the foreign exchange market. J Financ Econ 39(2–3):321–351
Ma D, Tanizaki H (2022) Intraday patterns of price clustering in bitcoin. Financ Innov 8(1):4. https://doi.org/10.1186/s40854-021-00307-4
Miwa K (2019) Trading hours extension and intraday price behavior. Int Rev Econ Financ 64:572–585. https://doi.org/10.1016/j.iref.2019.07.007
Miwa K, Ueda K (2017) Is the extension of trading hours always beneficial? An artificial agent-based analysis. Comput Econom 50(4):595–627. https://doi.org/10.1007/s10614-016-9613-0
Moex (2019) Moscow Exchange's FX Market. Retrieved from https://www.moex.com/en/markets/currency/. Retrieved 20.12.2019
Nakatsuma T, Tsurumi H (1996) Arma-Garch Models: Bayes Estimation Versus Mle, and Bayes Non-Stationarity Test. Retrieved from https://www.econstor.eu/bitstream/10419/94323/1/1996-19.pdf. Retrieved 03.03.2021
Omrane WB, Welch R (2016) Tick test accuracy in foreign exchange ecn markets. Res Int Bus Financ 37:135–152
Pan Q, Mei X, Gao T (2022) Modeling dynamic conditional correlations with leverage effects and volatility spillover effects: evidence from the chinese and us stock markets affected by the recent trade friction. North Am J Econom Finance 59:101591. https://doi.org/10.1016/j.najef.2021.101591
Panayides MA, Shohfi TD, Smith JD (2019) Bulk volume classification and information detection. J Bank Finance 103:113–129. https://doi.org/10.1016/j.jbankfin.2019.04.001
Park SG, Suen W, Wan K-M (2022) Call auction design and closing price manipulation: evidence from the HONG kong stock exchange. J Financ Mark 58:100700. https://doi.org/10.1016/j.finmar.2021.100700
Parkinson M (1980) The extreme value method for estimating the variance of the rate of return. J Bus:61–65
Patton AJ, Sheppard K (2015) Good volatility, bad volatility: signed jumps and the persistence of volatility. Rev Econ Stat 97(3):683–697. https://doi.org/10.1162/REST_a_00503
Paye BS (2012) 'Déjà Vol': predictive regressions for aggregate stock market volatility using macroeconomic variables. J Financ Econ 106(3):527–546. https://doi.org/10.1016/j.jfineco.2012.06.005
Phillips PCB, Perron P (1988) Testing for a unit root in time series regression. Biometrika 75(2):335–346. https://doi.org/10.1093/biomet/75.2.335
Pöppe T, Moos S, Schiereck D (2016) The sensitivity of vpin to the choice of trade classification algorithm. J Bank Finance 73:165–181. https://doi.org/10.1016/j.jbankfin.2016.08.006
Qiu Y, Zhang X, Xie T, Zhao S (2019) Versatile Har model for realized volatility: a least square model averaging perspective. J Manag Sci Eng 4(1):55–73. https://doi.org/10.1016/j.jmse.2019.03.003
Rogers LCG, Satchell SE (1991) Estimating variance from high, low and closing prices. Ann Appl Probab 1(4):504–512. https://doi.org/10.1214/aoap/1177005835
Savickas R, Wilson AJ (2003) On inferring the direction of option trades. J Financ Quant Anal 38(4):881. https://doi.org/10.2307/4126747
Schwert GW (1989) Why does stock market volatility change over time? J Financ 44(5):1115–1153. https://doi.org/10.1111/j.1540-6261.1989.tb02647.x
Seemann L, McCauley JL, Gunaratne GH (2011) Intraday volatility and scaling in high frequency foreign exchange markets. Int Rev Financ Anal 20(3):121–126. https://doi.org/10.1016/j.irfa.2011.02.008
Sensoy A, Serdengecti S (2019) Intraday volume-volatility nexus in the FX markets: evidence from an emerging market. Int Rev Financ Anal 64:1–12. https://doi.org/10.1016/j.irfa.2019.04.001
Sévi B (2014) Forecasting the volatility of crude oil futures using intraday data. Eur J Oper Res 235(3):643–659. https://doi.org/10.1016/j.ejor.2014.01.019
Smolović JC, Lipovina-Božović M, Vujošević S (2017) Garch models in value at risk estimation: empirical evidence from the montenegrin stock exchange. Econ Res-Ekonomska Istraživanja 30(1):477–498. https://doi.org/10.1080/1331677X.2017.1305773
Su F (2021) Conditional volatility persistence and volatility spillovers in the foreign exchange market. Res Int Bus Finance 55:101312. https://doi.org/10.1016/j.ribaf.2020.101312
Tauchen G, Zhang H, Liu M (1996) Volume, volatility, and leverage: a dynamic analysis. J Econom 74(1):177–208. https://doi.org/10.1016/0304-4076(95)01755-0
Taylor SJ (1986) Modelling financial time series. Wiley
Todorova N, Souček M (2014) Overnight information flow and realized volatility forecasting. Financ Res Lett 11(4):420–428. https://doi.org/10.1016/j.frl.2014.07.001
Viola AP, Klotzle MC, Pinto ACF, da Silveira Barbedo CH (2019) Foreign exchange interventions in brazil and their impact on volatility: a quantile regression approach. Res Int Bus Financ 47:251–263. https://doi.org/10.1016/j.ribaf.2018.08.002
Wang Y, Ma F, Wei Y, Wu C (2016) Forecasting realized volatility in a changing world: a dynamic model averaging approach. J Bank Finance 64:136–149. https://doi.org/10.1016/j.jbankfin.2015.12.010
Wang Y, Wei Y, Wu C, Yin L (2018) Oil and the short-term predictability of stock return volatility. J Empir Financ 47:90–104. https://doi.org/10.1016/j.jempfin.2018.03.002
Wiphatthananthakul C, Sriboonchitta S (2010) The Comparison among Arma-Garch,-Egarch,-Gjr, and-Pgarch Models on Thailand Volatility Index. Thailand Econom Soc 2(2):140–148

Yung C (2005) Insider trading with private information and moral hazard. Financ Res Lett 2(2):51–57. https://doi.org/10.1016/j.frl.2005.04.003
Zhang H (2018) Intraday patterns in foreign exchange returns and realized volatility. Financ Res Lett 27:99–104. https://doi.org/10.1016/j.frl.2018.02.017
Zhang W, Yan K, Shen D (2021) Can the Baidu index predict realized volatility in the Chinese stock market? Financ Innov 7(1):7. https://doi.org/10.1186/s40854-020-00216-y

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