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Strength of words: Donald Trump's tweets, sanctions and Russia's ruble

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ABSTRACT

We empirically test if the US President Donald Trump's rhetoric towards Russia (represented by his Russia-related tweets) affects ruble's exchange rate. Using three-stepped empirical framework, we find that escalation of negative sentiment of Trump's Russia-related tweets leads to ruble's depreciation (4–10%) in short-term periods (around 3 days). Though these episodes tend to coincide with imposition or announcement of US sanctions, we demonstrate that US sanctions that were not accompanied by negative tweets of Donald Trump, have not caused ruble's depreciation. This highlights the role of emotional factors in economic decision-making behavior.

1. Introduction

With the rise of social media, more and more people use social media platforms such as Twitter, Facebook, Reddit for either sharing or getting new information including business, economic and financial information. Does this "online" information affect market agents in a similar way compared to more traditional kinds of information? Does this impact depend on the characteristics of individuals sharing the information? Regarding the first question, there is rather vast literature that analyzes the influence of social media on financial markets.[1] Virtually all relevant studies focus on the effects of social media messages (primarily tweets) of numerous heterogeneous individuals treating them as private information (see, e.g., Bollen et al., 2011; Zhang et al., 2011; Mittal and Goel 2012; Nofer and Hinz 2015; Bartov et al., 2018; Gholampour and Van Wincoop 2019). Regarding the second question, to the best of our knowledge, there is only one study of Yang et al. (2015) that suggests that this impact largely depends on the degree of forcefulness of the social media platform user (particularly, Twitter user). In this study, we continue developing this line of thinking and empirically test if the sentiment of the US President Donald Trump's tweets on Russia-related issues affects Russian ruble exchange rate.

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[1] For detailed literature review, see Reboredo and Ugolini (2018).

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The importance of information arrival for the determination of exchange rates is well established through the FX microstructure literature that emerged in the 1990s in response to the disappointing empirical performance of macro-based exchange rate models (Meese and Rogoff 1983a; Meese and Rogoff 1983b).[2] Since information can be private and public, relevant theory also distinguishes between the effects of information of different types (see, e.g., French and Roll 1986). Though most relevant studies treat tweets (of heterogeneous individuals) as private information, we show that tweets of the acting American president, due to their significant media resonance, are largely treated as public information or news. In respect that empirical literature on the effects of public information arrival on exchange rates has generally focused on the effects of various macroeconomic announcement and traditional kinds of economic/policy news,[3] the first novel aspect of our paper is to use tweets of a bigtime politician as the source of public information.

Several arguments support our belief in a distinct impact of Donald Trump's tweets on the Russian ruble. First, Donald Trump is the acting US president and, thus, his tweets are *per se* expected to have significant policy impact. Second, significantly increased political tensions between Russia and USA since 2014 (due to the political and military conflict between Russia and Ukraine) have escalated the dependence of Russia and its economy on the World politics and particularly on the US-Russia relations. Since 2014 Russia is the subject of a sanctions' regime imposed in a coordinated move by the US and the EU, and by other Western allies. Though the sanctions were imposed by all Western countries, USA obviously leads this process. Hence, considering these new political conditions, it is plausible to suggest that agents in financial markets including FX market take into consideration the US President's rhetoric towards future direction of US-Russia relations.

Furthermore, we argue that in the present political situation the US president's rhetoric towards Russia can represent an alternative measure of US sanctions' policy against Russia. Dreger et al. (2016) studied the effects of recent Western sanctions against Russia on Russian ruble's exchange rate dynamics measuring sanctions by a composite sanctions' index and sanctions' expectations - by a media news' index. They find that the effects of the sanctions' variables are only marginally significant. In this study, we suggest that the sentiment of Donald Trump's tweets on Russia-related issues might represent an alternative measure of early signs of the direction of US sanctions' policy towards Russia.

Finally, recent financial and economic research suggests that political uncertainty can have significant negative economic and financial effects (see, e.g., Bittlingmayer 1998; Goretti 2005) and can even lead to a financial crisis in an emerging market (Mei and Guo 2004). In the context of our study, we propose that particularly escalation of the rhetoric with negative sentiment of the acting US president towards Russia can significantly increase political uncertainty in Russia that, in turn, increases uncertainty of economic agents about the direction of the development of country's macroeconomic fundamentals. Ultimately, it can cause Russian currency to depreciate.

We take several steps to connect Donald Trump's tweets and Russian ruble exchange rate. We start by selecting Donald Trump's tweets which could affect Russian ruble exchange rate in the period from 03.10.2016 to 31.08.2018. We then classify selected tweets as showing positive, negative or neutral sentiment. To evaluate tweets' sentiment, we utilize a widely used lexicon-based approach separately using five well-recognized lexicons. We further argue that Trump tweets' effects for economic agents' behavior can persist over certain period and utilize seven decay schemes in computing sentiment variables. In such a way we end up with 35 alternative sentiment variables. We also consider several control variables. Then we use the elastic net regression (Zou and Hastie 2005)[4] to select the variables that will be included into our core empirical analysis.[5] Elastic net selects oil price, direct index of US sanctions and Trump tweets' sentiment indicators as significant factors of Russian ruble exchange rate dynamics. In the next step, we estimate ARIMA-GARCH regression with variables chosen by elastic net.

Though the above methodology allows us to evaluate the averaged over time impact of Donald Trump's tweets on ruble's exchange rate, we further propose a framework that enables us to reveal certain periods when this impact has been indeed notable and their duration. More specifically, we suggest that Russian ruble's exchange rate is determined by two approaches, which relative importance varies over time. According to the first approach (we name it "economic regime"), the exchange rate is determined by country-specific economic fundamentals (in our case by oil price) and according to the second (we name it "political regime") - by sanctions and arrival of essential political information (information is represented by Trump's tweets' sentiment). For estimation, we utilize Markov regime-switching (MRS) model.

In summary, we can say that though both regimes are well identified in MRS model, oil price (the only economic variable (fundamental) chosen by elastic net) remains the main long-term determinant of ruble exchange rate. The political regime is fully determined by Trump's tweets' sentiment while US sanctions' direct index is insignificant. The impact of Trump's tweets' sentiment tends to be episodic and short-term. Significant toughening of Trump's Twitter Russia-related negative rhetoric can lead to short-term (around 3 days) "abruptions" in the process of ruble exchange rate's formation based on oil price causing significant depreciation of the Russian ruble.

However, the qualitative analysis of the episodes of "political regime" has revealed that all three detected episodes coincide with imposition or announcement of new US sanctions against Russia. Furthermore, virtually all Russia-related tweets

[2] Reviews of the FX microstructure literature can be found in Lyons (2001), Evans (2011), Evans and Rime (2012), King et al. (2013).

[3] See Cornell (1982), Hardouvelis (1988), Ederington and Lee (1993), Ederington and Lee (1995), Almeida et al. (1998), Andersen et al. (2003), Dominguez and Panthaki (2006), Faust et al. (2007), Chen and Gau (2010), Gau and Wu (2017), Ederington et al. (2019) among others.

[4] A regularization technique that does automatic variable selection and can select groups of most relevant explanation variables.

[5] Sarno and Valente (2009) similarly employ a recursive model selection procedure when they select the best model of exchange rate based on a variety of criteria across all possible combinations of fundamentals.

of Donald Trump of two out of three detected episodes of “political regime” are linked to the discussion of possible collusion of Donald Trump with Russia. Since Trump’s opponents, accusing him in colluding with Russia, that way make a pressure on him to impose new sanctions on Russia, such tweets (with negative sentiment) signal to FX market agents about high probability of new US sanctions that in turn causes Russia’s currency to depreciate.

Finally, detailed analysis of all episodes of the US sanctions in the studied period demonstrates that those sanctions’ episodes, which do not coincide with the periods of “political regime” identified by Markov regime-switching model and, hence, were not accompanied by Russia-related tweets of Donald Trump with significant negative sentiment, have not caused sharp depreciation of Russian currency. This further suggests that market agents assess the seriousness of the sanctions (i.e. their potential damage for Russia) by emotional reactions in mass media, including Twitter of the US president.

In general, our findings confirm previous literature that concluded that recent Western sanctions *in themselves* did not have significant negative effects on the Russian economy (Gurvich and Prilepskiy 2015; Dreger et al., 2016; Korhonen et al., 2018). According to our study, it seems that particularly emotional-expression component of the sanctions has had negative effects on Russian ruble. However, these findings are not surprising. Indeed, initially, Western countries (led by USA) did not aim to hurt significantly the whole Russian economy but rather aimed to affect President Putin’s policy towards Ukraine via so-called “smart” sanctions that would primarily have negative effects for individuals and companies that actively support Putin’s presidency (see, for example, Gilligan 2016).

This paper is related to three strands of literature. First, our study contributes to the vast research that studies the effects of various news and announcements on exchange rate (see footnote 3). Second, it relates to the literature that has used messages from social media and the internet (particularly tweets) to predict asset prices.[6] However, to the best of our knowledge, there are only two studies, Gholampour and Van Wincoop (2019) and Ozturk and Ciftci (2014), which empirically analyze the effects of tweets on exchange rate dynamics. Both papers analyze the impact of tweets of numerous heterogeneous individuals while in this study we focus on the impact of tweets of one bigtime politician. Finally, the paper contributes to the limited literature on the impact of sanctions on sanctioned economies (Neuenkirch and Neumeier 2015; Afesorgbor and Mahadevan 2016; Dreger et al., 2016; Neuenkirch and Neumeier 2016; Tuzova and Qayum 2016).

The paper is organized as follows. In the next section, we put forward our research question based on a structured discussion of related literature and outline theoretical framework for our empirical analysis. Section 3 describes our methodology and data. Section 4 presents and discusses the results including qualitative analysis of "political/sentiment regime" episodes and various robustness-checking. Section 5 concludes.

2. Background

Twenty-five years after the fall of the Iron Curtain, the current crisis in relations between Russia and the West represents a major setback that is also evolving into a dangerous geopolitical conflict (Havlik 2014). The crisis started in 2014 in the aftermath of the pro-European revolution in Ukraine and has caused severe political tensions between the West (particularly the US and the EU) and Russia, which remain until present moment. In response to Russia’s annexation of Crimea and support for separatist rebels in Eastern Ukraine, in 2014 the United States, the EU, and several other countries imposed diplomatic and economic sanctions on Russia. Up to present moment, the sanctions have been continuously renewed and enlarged several times.

To the best of our knowledge, there is only one study by Dreger et al., 2016 that attempted to empirically evaluate the effects of recent sanctions on Russian Ruble exchange rate. Based on impulse response analysis and variance decomposition, Dreger et al. show that while unanticipated component of sanctions matters for the conditional volatility of the variables involved, the bulk of the exchange rate depreciation can be attributed to declining oil prices. Dreger et al.’s general conclusion is that a short-term effect of sanctions on the ruble’s exchange rate is absent.

In this study, we suggest that sanctions’ impact on Russian ruble could be more visible if we explicitly detach the emotional component of sanctions’ policy. Since sanctions against Russia have been largely led by the US, we further propose that the sentiment of the US President’s rhetoric towards Russia can represent a valid measure of the sanctions’ emotional component. We further utilize the US president’s Russia-related tweets to evaluate his rhetoric towards Russia.

2.1. An increasing role of Twitter in the news industry

In recent times, the emergence of online social media (Twitter, Facebook, Reddit) has transformed the news industry in many unforeseen ways. Traditional news providers have been assaulted by one disruption after another from people sharing news on social media including a tweeting President. Furthermore, as the social media platforms are "always-on", they fast became key platform for collating updates, gathering comments and reporting breaking news (Orellana-Rodriguez and Keane 2018). Twitter also plays an increasingly prominent role in disseminating information on financial markets in real time (Bukovina 2016) and affects investment decisions (Chen et al., 2014; Ma and Chan 2014).

Politicians throughout the democratic world have begun to embrace social networking tools such as Twitter and Facebook as a new way to connect with their constituents, shortcutting the heavily mediated connections offered by traditional media

[6] For detailed literature review, see Reboredo and Ugolini (2018).

(Grant et al., 2010). The successful use of social media in the US presidential campaigns of Barack Obama and Donald Trump has established Twitter, Facebook, MySpace, and other social media as integral parts of the political campaign toolbox and their role in Big politics was virtually equaled to the role of traditional media (Tumasjan et al., 2010; Morris 2018). Furthermore, the messages of politicians often serve as raw materials for the mainstream media (Lee and Shin 2012). In a similar vein, this study suggests that tweets of a politician can have comparable effects on the public (and economic agents, in particular) as traditional media news.

2.2. Tweets as the source of information and financial markets

Since Meese and Rogoff (1983a), Meese and Rogoff (1983b), Meese and Rogoff (1988), it has been well known that exchange rates are difficult to predict using economic fundamentals.[7] Because structural models have failed to predict most of the variation in exchange rates in the 1970s, the role of information, private and public, has gained importance in the exchange rate literature since then.

In one respect, tweets represent private information and there is ample theoretical research on the role of private information in financial markets (see, e.g., Grossman 1976; Diamond and Verrecchia 1987; Holden and Subrahmanyam 1992) including FX market (Bacchetta and Van Wincoop 2006). In recent years sizable empirical research has emerged that treats tweets of individuals as private information and tests their impact (mood, sentiment or content of tweets) on financial markets, particularly asset/stock prices (see, e.g., Bollen et al., 2011; Zhang et al., 2011; Mittal and Goel 2012; Meinusch and Tillmann 2015; Nofer and Hinz 2015; Azar and Lo 2016; Bartov et al. 2018; Zhang et al., 2018). In relation to FX market and exchange rate dynamics, Gholampour and Van Wincoop (2019) estimate the private information model of Bacchetta and Van Wincoop (2006) for USD-EUR exchange rate with Twitter opinions representing private information. Recent research has further suggested that the impact of tweets on financial markets largely depends on the degree of forcefulness of the Twitter user (Yang et al., 2015). In this study, we continue to develop this line of thinking focusing on one of the top Twitter influencers, the US president Donald Trump.

However, the question arises what type of information the tweets of the acting American president represent. Indeed, it is more plausible to associate the Twitter account of the acting president with 85.4 million followers with public rather than private information. Furthermore, on 23rd of May 2018 a district court in New York has ruled that Donald Trump cannot block people on Twitter, because it violates their first amendment rights to participate in a "public forum". In ruling against Trump, the court pointed to past White House assurances that the president's Twitter account is an official political channel. Thus, in this study we treat Donald Trump's tweets as public information.

2.3. Research question

The basic research question of this study is how the sentiment of the US President Donald Trump's tweets on Russia-related issues affects Russian ruble's exchange rate dynamics. Its importance is dual. On the one hand, given Russia's heavy dependence on commodity exports, foreign investment and imports of consumer goods, exchange rate fluctuations strongly affect the Russian economy (Dreger et al., 2016). On the other hand, the current geopolitical tensions between Russia and the West (and the US, in particular) raises the importance to investigate economic consequences of these tensions.

President Donald Trump joined Twitter in March 2009 and currently is running both a personal and an official Twitter account as leader of the United States. Trump's frequent use of Twitter in the addressing of individual companies, countries and future U.S. policy towards commerce have made his Twitter feed an influential market moving force (Markets, 2017). Several studies have already confirmed significant effects of Donald Trump's tweets on stock markets (see Born et al., 2017; Ge et al., 2019).

In a broader perspective, the impact of the US policy announcements on emerging markets has already gained significant attention in earlier literature. More specifically, numerous research articles have been studying the transmission of Federal Reserve tapering news to emerging markets (see, e.g., Mishra et al., 2014; Lavigne et al., 2014; Chari et al., 2017; Medvedev et al., 2019). In general, these studies show that US Federal Reserve tapering news significantly affect capital flows, asset prices and exchange rates in emerging markets causing in many cases financial and economic crises. To a certain extent, some of the US President's tweets can be considered as a special type of such policy announcements and, hence, researching their impact on an emerging country such as Russia appears reasonable. Furthermore, significant geopolitical tensions between Russia and USA in recent years (including sanctions) makes this impact even more likely. Specifically, we suggest that the sentiment of Russia-related tweets of the acting US president largely reflects (de-)escalation of the current geopolitical conflict between Russia and the West (particularly USA) this way affecting the Russia-related decisions of economic agents and investors in financial markets (including foreign exchange market).

[7] Rossi (2013) provides an extensive summary of economic predictors of exchange rates used in the literature. They include so-called traditional predictors (interest rate, price and inflation, money and output, productivity differentials, portfolio balance), Taylor rule fundamentals, external balance measures and commodity prices.

2.4. Basic framework of empirical analysis: regime-switching technique

There is ample research applying regime-switching technique to study exchange rate dynamics. Engle and Hamilton (1990) were the first to adopt the Markov regime-switching approach suggested by Hamilton (1989) to model exchange rate. Recent research has further documented the successful use of Markov switching models to study the exchange rate dynamics (see, e.g., Bollen et al., 2000; Dewachter 2001; Frömmel et al., 2005; Lee and Chen 2006; Bailliu et al., 2014; Wu 2015).

In this paper, we suggest that, in the light of current economic and political conjuncture formed in Russia, the exchange rate of Russian currency is determined by two approaches, which relative importance varies over time. We name the first approach as "economic" assuming that the exchange rate is determined by economic fundamentals. According to the second approach (we name it "political"), sanctions and arrival of public information of high magnitude determine the ruble's exchange rate dynamics. We further propose that particularly arrival of public information with essentially large negative sentiment can significantly increase political uncertainty in Russia that, in turn, causes the switching of exchange rate regime from "economic" to "political" and leads to a sharp and large depreciation of the Russian currency.

3. Methodology and data

3.1. Dependent and control variables

Our dependent variable is the exchange rate of Russian ruble in a day t in the period from 03.10.2016 to 31.08.2018.[8] The initial date is the date one month before Trump was elected as president of the US. We suggest that from this moment his tweets could affect Russian currency market. For measuring our dependent variable, we utilize spot exchange rates of Russian ruble into dollar published by Bank of England. These are indicative middle market (mean of spot buying and selling) daily rates as observed by the Bank's Foreign Exchange Desk in the London interbank market around 4pm. They are not "official" rates and are no more authoritative than rates provided by any commercial bank operating in the London market. In comparison with official exchange rate of the Russian Central Bank, this indicator reflects daily spot price of the ruble, which formed directly on the international foreign exchange market. We excluded weekends as Bank of England does not report exchange rates on weekends.

We include six control variables in our preliminary specification. First, we control for oil price in the world market (denoted by p_t) that is widely accepted as an important factor of exchange rate dynamics of Russian ruble (see, e.g., Rautava 2004; Dreger et al., 2016). We measure it by the reference price for the OPEC crude oil basket (OPEC Reference Basket).

Second, though from 2014 the Russian Central Bank has switched to a floating exchange rate policy for the Russian ruble, thereby ending the policy of currency band, it still uses some indirect tools to soften ruble depreciation in the moments of its significant devaluation. One of such tools is RUONIA (Ruble Over Night Index Average), indicative factored rate of one-day ruble credits reflecting the value of cost of uncovered ruble borrowing under the terms of "overnight" for borrower from Russian banks with minimal credit risk. We further need to count for a benchmark interest rate at which major global banks lend to one another in the international interbank market for short-term loans such as LIBOR. Hence, we include RUONIA over LIBOR rate differential as a control variable in our model and denote it by r_t (see also Dreger et al., 2016). The data comes from the RUONIA and LIBOR websites.

Third, we control for Western sanctions against Russia. We include three sanctions' indices – US sanctions' index, European Union sanctions' index and other countries' sanctions' index (denoted as d_t^{us}, d_t^{eu} and d_t^{ot}, accordingly). To compute the indices, we used Dreger et al. (2016) approach though we did not count for Russia's countersanctions and did not weight countries by trade volume since we use three independent country-specific indices.

Fourth, to count for other media coverage's effects on economic agents' behavior, and, consequently, ruble's exchange rate, we also include news' index that reflect intensity of the polemics on Western sanctions against Russia in global media (denoted as N_t). To compute the index, we used all Russia-related news in the studied period from the official website of Thomson Reuters news agency. For this we used different word forms of the word “Russia”. From the obtained news we select the sanctions-related news using different word forms of the word “sanctions”. The final index was computed as the daily share of sanctions-related news in the total number of Russia-related news (in percent).

On Fig. A1 in Appendix A we depict these variables in dynamics for the studied period. ADF and KPSS tests have shown that our dependent and control variables are non-stationary (top panel of Table 1). To make Ruble-USD exchange rate and oil price stationary, we transformed them into natural logarithm and took their first differences (i.e. convert to log-return). To make RUONIA over LIBOR rate, sanctions' and news' indices stationary we took the first difference. The resulted variables are stationary (bottom panel of Table 1).

[8] It should be noted that we base our empirical analysis on the daily rather than hourly data due to several reasons. First, one third of Trump's tweets have been published on weekends and, hence, cannot be directly integrated into hourly data framework. Second, the association of some of our control variables (in particular, sanctions' indices) with Russian ruble exchange rate is better to study within daily data framework. Finally, previous research on the relationship between tweets and exchange rate is based on daily exchange rate data (Ozturk and Ciftci 2014; Gholampour and Van Wincoop 2019).

Table 1
Stationarity tests of the dependent and control variables.

Variable	ADF-test			KPSS-test		
	Statistics	*p*-value	Lag	Statistics	*p*-value	Lag
Initial variables						
Ruble-USD exchange rate	−1.088	0.92	7	1.266	0.01	5
OPEC reference basket &	−2.701	0.28	7	1.147	0.01	5
RUONIA over LIBOR rate	−2.584	0.33	7	0.670	0.01	5
Sanction index - USA	−2.114	0.53	7	1.265	0.01	5
Sanction index - Europe	−2.613	0.33	7	0.568	0.01	5
Sanction index - Other	−2.779	0.25	7	0.325	0.01	5
News index	−3.573	0.04	7	0.625	0.02	5
Transformed variables						
Ruble-USD exchange rate (log-return)	−8.197	0.01	7	0.449	0.06	5
OPEC reference basket (log-return)	−7.299	0.01	7	0.075	0.10	5
RUONIA over LIBOR rate (first difference)	−10.818	0.01	7	0.050	0.10	5
Sanction index - USA (first difference)	−7.512	0.01	7	0.077	0.10	5
Sanction index - Europe (first difference)	−7.794	0.01	7	0.044	0.10	5
Sanction index - Other (first difference)	−11.644	0.01	7	0.434	0.06	5
News index (first difference)	−10.664	0.01	7	0.014	0.10	5

Notes: 1) Null hypothesis of ADF-test: at least one unit root is present in a time series sample (model with constant and trend); 2) Null hypothesis of KPSS-test: an observable time series is stationary around a deterministic trend.

3.2. Explanatory variables

As our explanatory variables, we include different measures of sentiment of Russia-related tweets of the US President Donald Trump. The tweets were collected from the official Twitter account of the US President Donald Trump, *@realDonaldTrump*. In the studied period, Donald Trump has published 5548 tweets. Prior to textual analysis of the tweets, all contractions in the tweets were extended to their full form (for example, «doesn't» to «does not») and all tweets have been cleaned from special characters, html markup, web links, user tags, selected hashtags (excluding those that have been used in the tweets rather often, for example, #makeamericagreatagain, #maga, #americafirst, #fakenews,etc.; such hashtags have been modified into equivalent phrases, for example, #maga was substituted by «make America great again»). We further excluded Fry's 25 most commonly used English words (Fry 1997) augmented with additional 13 words and contractions that, in our view, do not contain obvious emotional context.

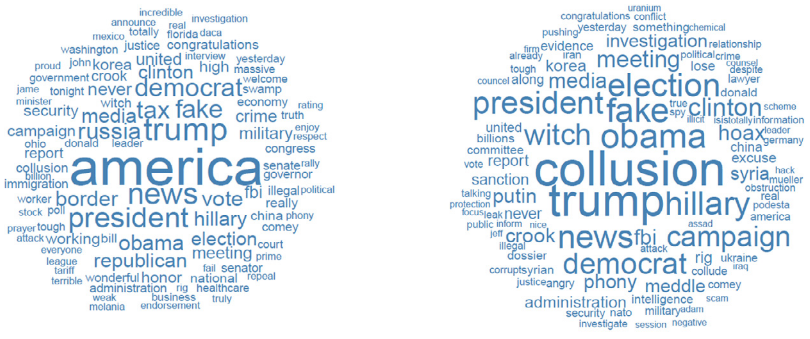
However, subjects of Trump's tweets are very different and obviously not every tweet could potentially affect Russian ruble exchange rate. Considering this, we have selected only relevant tweets using certain key words (including derivative words formed from them): Russia, Moscow, Kremlin, Putin, Medvedev, ruble, sanction, Ukraine, Crimea, Syria, oil price, *PutinRF_Eng, MedvedevRussiaE*.[9] As a result, we have chosen 316 tweets. Next, we carefully have read all selected tweets and deleted those tweets, which still do not relate to Russia. More specifically, several tweets related to sanctions in North Korea and Iran have been selected based on the key word "sanctions". In addition, several tweets discussing very general issues (e.g. drug trade) were also chosen. After removing these tweets, we end up with 296 tweets. On Fig. 1 we further present word clouds of Donald Trump's tweets, both all and only Russia-related.

If we consider all tweets, the most frequently mentioned word is America followed by president, Trump, democracy and news. In Russia-related tweets, the most frequent word is collusion followed by Hillary, Obama, fake and elections. Indeed, 165 out of 296 selected tweets (56 percent) were identified as related to the discussion about collusion between Trump and Kremlin in the US President's elections. Only two tweets mentioned sanctions against Russia directly and few other tweets can be considered as directly signaling about certain US policy change towards Russia (though still with a stretch). The remaining Russia-related tweets represent emotional reaction of Donald Trump towards Russia-related issues in general.

Time of tweets' publications has been converted into GMT time zone. Since our dependent variable is the spot exchange rate of Bank of England, which is published daily at 4pm, the daily tweets were assigned between 4pm of each day. As exchange rates are not reported on weekends though tweets are published on weekends (about one third of relevant Trump's tweets in our study were published on weekends), weekend tweets were transferred to the nearest Monday considering it as a day of tweet publication.

To evaluate the sentiment of tweets we have employed a widely used "bag-of-words"/lexicon-based approach. The idea of this approach is that we treat each text as the set of independent words (i.e. "the bag"), each of which can be classified

9 Last two words are names of official Twitter accounts of the Russian President Vladimir Putin and Russian Prime Minister Dmitri Medvedev. Hence, we also included those Trump's tweets which have references to the respective accounts of the Russian President and Prime Minister. However, it should be noted that on November 28 of 2018 (i.e. three months after our studied period ends) Twitter have made an announcement that *PutinRF_Eng* was suspended for impersonation based on a valid report they received from Russian officials. In spite of this, we decided to remain *PutinRF_Eng* as a key word since until November 2018 it was widely considered as official account of Russian President Vladimir Putin.



All tweets *Russia-related tweets*

Fig. 1. Words clouds of Donald Trump's tweets (100 most frequent lemmatized words, the size of font is proportional to frequency).

Table 2
Main characteristics of the lexicons used in the study.

Lexicon	Notation	Number of words		
		Negative	Neutral	Positive
Harvard General Inquirer (Harvard IV-4 united with Laswell)[a)]	GI	3695	0	2550
Loughran and McDonald (2011)[b)]	LM	2350	0	352
NRC of Mohammad and Turney (2010)[c)]	NRC	3241	0	2227
SentiWordNet of Baccianella et al. (2010)[d)]	SWN	11,029	166	8898
United lexicon of Jockers (2017) and Hu and Liu (2004), complemented by Rinker (2018)[e)]	JR	7818	13	3878

The online sources of lexicons: a)http://www.wjh.harvard.edu/~inquirer/homecat.htm; b)https://sraf.nd.edu/textual-analysis/resources/\#Master\%20Dictionary; c)http://www.purl.com/net/lexicons; d)http://sentiwordnet.isti.cnr.it; e)http://github.com/trinker/lexicon.

as positive, neutral or negative based on the list of words formed beforehand, which is called lexicon. This lexicon contains certain words and coefficients, which characterize their sentiment. In general, there are two main types of such lexicons: in the first one, sentiment is expressed as negative (−1), neutral (0) or positive (+1) (in some cases, neutral (0) can be absent). In the second one, sentiment is measured by factionary values which reflect somewhat higher degree of sentiment's granularity.

Up to date, fair number of lexicons were developed. However, there is no single comprehensive lexicon, which could be considered as standard. With that, every lexicon consists of differing set of words and might count for somewhat differing topics. Hence, a priori choice of one of them carries a risk of getting inaccurate results since computed sentiments might differ significantly between lexicons. Taking this into consideration, we use five lexicons that have commonly been used in previous studies on text sentiment analysis. In Table 2, we report their main characteristics.

For each lexicon l (see column "Notation" in Table 2), sentiment of a tweet n, published on a date t is computed as difference between number of positive $N^{+}_{n,t,l}$ and negative $N^{-}_{n,t,l}$ words, divided by total number of words in the text ($N^{0}_{n,t,l}$ is number of neutral words):

$$S_{n,t,l} = \frac{N^{+}_{n,t,l} - N^{-}_{n,t,l}}{N^{+}_{n,t,l} + N^{0}_{n,t,l} + N^{-}_{n,t,l}}. \tag{1}$$

In cases when words' sentiment in a lexicon is measured by fractional values of positiveness or negativeness (in particular, SWN and JR lexicons assign such values/scores while GI, LM and NRC lexicons just classify words as positive and negative), $N^{+}_{n,t,l}$ and $N^{-}_{n,t,l}$were computed as the sum of positive or negative scores, respectively.

To aggregate sentiment of several tweets during the same day, we have computed their weighted average with weights $w_{n,t}$, proportional to the tweets' length (length of a tweet n divided by total length of relevant tweets during day t):

$$S_{t,l} = \sum_{n} w_{n,t} S_{n,t,l}. \tag{2}$$

Following Ardia et al. (2020), Ardia et al. (2019), we further suggest that tweets' effects for economic agents' behavior is inertial and can persist during certain period. Moreover, in the current situation of geopolitical tensions between Russia and the US, the duration of the effects' impact can further prolong as the tweets might signal about long-term worsening/improving of the relations between the countries, new sanctions or weakening/lifting the sanctions. Though the effects are expected to be inertial, we assume that they fade over time. In this study, we assume that the decay period τ equals to 7 days (one working week and two days of next week). Upon that, we consider three basic decay schemes ($t = 1, \ldots, \tau - 1$):

- equal weights (i.e. no decay), *ew*: v_t=1;

Table 3
Descriptive statistics of averaged sentiment of Russia-related tweets of Donald Trump.

Statistics	Decay schemes and lexicons	Decay schemes	Lexicons
Mean	−0.0385	−0.0071	−0.0055
Standard deviation	0.0668	0.0114	0.0100
Median	−0.0246	−0.0045	−0.0031
Trimmed mean	−0.0349	−0.0063	−0.0049
Minimum	−0.2968	−0.0475	−0.0459
Maximum	0.1729	0.0353	0.0268
Range	0.4696	0.0828	0.0727
Skewness	−0.5066	−0.6306	−0.5180
Excess kurtosis	1.2248	1.5541	1.4794

Notes: "Decay schemes and lexicons" - sentiment variables averaged over all considered decay schemes and all lexicons; "Decay schemes" - Jockers–Rinker lexicon based sentiment variables averaged over all decay schemes, "Lexicons" - exponential decay (λ = 0.5) schema based sentiment variables averaged over all lexicons.

- linearly diminishing weights, *lw*: υ_t=1-t/ τ;
- exponentially diminishing weights, *exp(λ)*: $\upsilon_t = e^{-\lambda t}$.

Decay parameter λ for the last scheme was chosen in a range from 0.1 (the slowest decay) to 0.5 (the fastest decay) with 0.1 step (five values). Hence, in total we have seven decay schemes (no decay or equal weights, linear decay and five decay schemes with differing exponential weights). The final measure of tweets' sentiment during a day *t*, computed based on lexicon *l* and decay scheme *v*, is denoted by $S_{t,l,\upsilon}$.

On Fig. B1 in Appendix B we depict Donald Trump's tweets' sentiment patterns averaged over seven decay schemes and five lexicons. First, we can observe that in general Donald Trump's Russia-related tweets have rather volatile sentiment patterns: positive tweets can be followed by negative and vice versa though negative sentiment seems to be dominant. Second, as it was already discussed above, the choice of different lexicons can lead to rather different computed sentiments. For example, lexicon LM shows rather volatile sentiment pattern with the largest amplitude of fluctuations compared to other lexicons. On the other hand, lexicon SWN demonstrates mostly neutral sentiment. Besides, in some cases different lexicons give opposite sentiment. For example, in November 2017 in the same moment of time lexicons NRC and GI show positive sentiment while SWN, JR and LM - negative. Finally, sentiment patterns are relatively similar between different decay schemes.

We further report descriptive statistics of Donald Trump's Russia-related tweets' sentiment in Table 3.

In the first column, we report descriptive statistics of tweets' sentiment averaged over all decay schemes and lexicons. As we can observe, the sentiment tends to be more negative than positive (mean, median and trimmed mean are all negative). Moreover, negative value for the skewness indicates that data is skewed left, i.e. towards negative values and, hence, time series exhibits higher probability of negative sentiment. The excess kurtosis value over 0 indicates that the distribution is too peaked. In the second and third columns, we further report descriptive statistics of tweets' sentiment computed based on one lexicon (Jockers–Rinker) averaged over all decay schemes and based on one decay scheme (exponential time decay with decay parameter λ =0.5) averaged over all lexicons, respectively. As we can see, in general, the conclusions made for the descriptive statistics of universal average reported in the first column hold.

3.3. Variables selection

In conjunction with the foregoing, we need to overcome several challenges in the subsequent estimation analysis. First, because we compute our measures of tweets' sentiment using 5 lexicons and 7 decay schemes separately, we end up with 35 alternative sentiment variables (in addition to six control variables). This leads to high-dimensional sparse model for which the ordinary (for example, OLS) estimator is not optimal solution. Second, as expected, sentiment variables are highly correlated that leads to multicollinearity problem.

To overcome these issues and in order to get a parsimonious enough model we use the regularization technique - an elastic net (Zou and Hastie 2005). Using this approach, we estimate the parameters of the following linear model:

$$y_t = \sum_k a_k X_{t,k} + \sum_l \sum_\upsilon \beta_{l,\upsilon} S_{t,l,\upsilon} + \varepsilon_t. \tag{3}$$

It is performed by the minimization of the following composite function (variables must be preliminary standardized):

$$\underbrace{min}_{a_k,\beta_{l,\upsilon}} \frac{1}{T}\left(\sum_{t=1}^{T} - \sum\nolimits_k a_k X_{t,k} - \sum\nolimits_l \sum\nolimits_\upsilon \beta_{l,\upsilon} S_{t,\upsilon}\right)^2 + \gamma_1\left(\gamma_2\left[\sum_k a_k + \sum_l \sum_\upsilon \beta_{l,\upsilon}\right] + (1-\gamma_2)\left[\sum_k \alpha_k^2 + \sum_l \sum_\upsilon \beta_{l,\upsilon}^2\right]\right), \tag{4}$$

where t - time index, T - time-series length, y_t - modelled Russian ruble exchange rate (to US dollar; in log difference), $X_{t,k}$ - kth control variable (modified accordingly; as was explained above), α_k - the model's coefficient for kth control variable, $S_{t,l,v}$ - sentiment explanatory variable, computed based on lexicon l and decay scheme v, $\beta_{l,v}$ - the model's coefficient of sentiment variable $S_{t,l,v}$, ε_t - independent and identically distributed normal error with zero mean and variance of σ^2.

In Eq. (4), the first term is the ordinary quadratic loss function (the residual sum of squares) and second term adds regularization, introducing penalty for the number of explanatory variables. Parameter γ_1 is the coefficient of penalty (tuning or regularization parameter). For $\gamma_1 = 0$ we get the standard least squares estimator and for $\gamma_1 \to \infty$ all model coefficients tend to zero. The intermediate values of γ_1 allow to balance between minimizing the residual sum of squares and shrinking the coefficients towards zero and this way to perform automated variable selection.

It should be noted that the method of elastic net combines two coboundary approaches to regularization: Ridge regression (Hoerl and Kennard, 1970, square of L_2-norm of the model coefficients' vector) with $\gamma_2 = 0$ and LASSO regression (Tibshirani, 1996, L_1-norm of the model coefficients' vector) with $\gamma_2 = 1$. Values of γ_2 in the range from 0 and 1 allow to balance between these two methods of regularization.

To choose concrete values of parameters γ_1 and γ_2, we performed a grid search by minimizing the AIC, adapted for regressions with large number of explanatory variables (Zou et al., 2007). Parameter γ_2 varied from 0 to 1 with interval 0.05, and for each γ_2, 100 values of $\gamma_1$were generated according to the strategy suggested by Friedman et al. (2010). In total, we have had 2100 combinations of parameters.

It should be noted that our control variables could be involuntary excluded from the regularization term, thereby not participating in the selection process. However, they were included in the selection process in order to verify their impact on exchange rate as well.

3.4. Econometric models of exchange rate

3.4.1. Generalized autoregressive conditional heteroscedastic model

The elastic net based selection of variables allows us to determine potentially significant variables to be included into the model. However, when choosing the model specification, we need to count for the peculiar features of the dependent (target) variable. First, we need to test for the presence of autocorrelation and heteroscedasticity (or volatility clustering) in our dependent variable, log-return of the Russian ruble-US dollar exchange rate.

In order to test for autocorrelation, we conducted Ljung–Box "portmanteau" test that has shown that the null hypothesis of independence of the first five lags cannot be rejected at 5% significance level (the number of lags was chosen in accordance to the "continuous" duration of trade period – from weekend to weekend). For heteroscedasticity diagnostic, we have also used Ljung–Box test though we applied it to square and absolute values of exchange rate log-return. The test's results indicate that the null hypothesis on the independence of observations of time series for five lags is rejected at 5% significance level both for square ($\chi 2 = 214.3$, d.o.$f = 3$, p-value $<< 0.001$) and absolute ($\chi 2 = 78.9$, d.o.$f = 5$, p-value $<< 0.001$) values. The analysis of the corresponding autocorrelation functions (ACF) has shown that first three coefficients of ACF are statistically significant at 5% level. A visual analysis of log-return time series further confirmed the presence of volatility clustering or heteroscedasticity in the studied time series.

To count for the uncovered features of the dependent variable time series, in the further modelling we have been using ARMAX-GARCH model (the combination of autoregressive moving average with exogenous factors and generalized autoregressive conditional heteroscedastic model). However, since we have not found evidence on the presence of autocorrelation in the ruble exchange rate log-return time series, we did not include autoregression and moving average terms into ARMAX specification though we counted for control and sentiment explanatory variables. As for the GARCH specification, it is worth to note that to date a relatively large number of modifications was proposed (for review, see Ghalanos 2014). We have considered the most popular versions such as "standard" GARCH (Bollerslev 1986), exponential GARCH (Nelson 1991) and Glosten-Jagannathan-Runkle GARCH (Glosten et al., 1993). Besides, conditional distribution of innovations can be predetermined in different forms. In this study we have considered the following variants: normal, Student, generalized error distribution, as well as skew variants of these distributions (based on the transformations described in Ferreira and Steel (2006).

We have conducted several preliminary estimations of different combinations of the mentioned modifications of GARCH models and conditional distributions. Based on the information criteria (Akaike, Bayes, Hannan-Quinn) and models residuals diagnostic tests (weighted Ljung-Box test on standardized direct and squared residuals, adjusted Pearson goodness-of-fit test), exponential GARCH with skewed Student distribution was chosen as final specification. We further concluded that it is enough to include only first lag of innovations and variance to remove heteroscedasticity.

Thereby, our final specification, denoted as ARMAX(0,0)-eGARCH(1,1), looks as follows:

$$
\begin{aligned}
& y_t = \sum_k \alpha_k X_{t,k} + \sum_l \sum_v \beta_{l,v} S_{t,l,v} + \sigma_t \varepsilon_t, \\
& log\sigma_t^2 = c + (\varphi_1 \varepsilon_{t-1} + \eta_1(|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|)) + \psi_1 log\sigma_{t-1}^2, \qquad (5) \\
& \varepsilon_t \sim t(0, \nu, \xi),
\end{aligned}
$$

where σ_t^2 - conditional variance, c - constant of conditional variance model, φ_1, η_1, ψ_1 - coefficients of conditional variance model, $t(0, \nu, \xi)$ - skewed Student distribution with zero mean, scale ν and skewness ξ. One of the properties of the exponential GARCH is the ability to capture asymmetry of reaction of volatility to sign of innovation in the past (along with the asymmetry of news curve - the dependence of conditional variance on model error). Such effect is characteristic for the behavior of the returns in financial and exchange markets: it is plausible to expect stronger reaction of trade participants to ruble depreciation and, hence, return volatility of exchange rate will be higher than in the case of ruble appreciation. This ability of exponential GARCH largely explains its suitability for our data.

We further should note that though the final specification in the form of Eq. (5) is generalized in relation to control and sentiment variables, posteriori we included only those variables that have been preliminary selected by elastic net.

3.4.2. Markov regime-switching model

Regime-switching models have rather long history in empirical economic studies (see, e.g., Quandt 1958; Goldfeld 1973). Their main feature is that they allow discrete change of model parameters, i.e. switching of the studied phenomena from one condition to another. Herewith regime switching can be either deterministic or stochastic. Hamilton (1989) proposed to use Markov chain as unobserved process that determines the state of the system involved. This version of regime-switching model, known as Markov regime-switching model (MRS), has been widely used in applied economic research (see, e.g., among others Kim 1994; Hamilton and Lin 1996; Kim and Nelson 1999).

As was already mentioned in Section 2, MRS models have been widely used to study exchange rate dynamics (see, e.g., among others Engle and Hamilton 1990; Vigfusson 1997; Bollen et al., 2000; Wu 2015). According to the approach suggested in this paper (see Section 2.4) we distinguish between two regimes: "economic regime" ($s = 1$) when exchange rate dynamics is determined by economic fundamentals (in this study they are represented by oil price and RUONIA over LIBOR rate) and "political regime" ($s = 2$) when the exchange rate departs from its traditional fundamental drivers and political factors such as sanctions (represented by sanctions' and news' indices as discussed above) and emotional reaction of market agents to political information (represented by tweets of the US President Donald Trump) starts to govern its dynamics.

Considering the foregoing, our model is specified as follows:

$$y_{t,s} = \begin{cases} \sum\limits_k a_k X_{t,k}^{s=1} + \varepsilon_{t,s}, \ \ s = 1 \\ \sum\limits_j \alpha_j X_{t,j}^{s=2} + \sum\limits_l \sum\limits_\nu \beta_{l,\nu} S_{t,l,\nu} + \varepsilon_{t,s}, \ \ s = 2 \end{cases}, \tag{6}$$

where s is regime index, $\{p_t, d_t\}$ - control variables of economic regime $s = 1$, $X_{t,k}^{s=1} \in \{d_t^{us}, d_t^{eu}, d_t^{ot}, N_t\}$ - control variables of political regime $s = 2$, $S_{t,l,\nu}$ - sentiment variables (see Sections 3.1-3.2 for naming convention), α_k, α_j, $\beta_{l,\nu}$ - the model coefficients, ε_{ts} is independent and identically distributed normal error with zero mean and variation of σ_s^2. It should be noted that we still have the problem of too many highly correlated variables (especially it concerns “sentiment” variables) and, hence, for the sake of getting parsimonious model, we use the results of variables' selection based on elastic net.

Since the unobserved process is Markov, the probability of the system being in state i at the moment t, $\pi_{i,t} = \Pr(s_t = i)$, is a function of the state j at the moment of time t-1, i.e. the current state depends only on the previous moment of time. With that the transition of the system from one regime to another is determined by transition matrix **P**:

$$\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}, \tag{7}$$

where $p_{ij} = \Pr(S_t = i \mid S_{t-1} = j)$ is the probability of the system switching from the state j in the moment of time *t-1* to the state i in the moment of time t.

Like ARMAX-GARCH model, the employment of MRS model allows to count for the heteroscedasticity of log-returns of the exchange rate that we have diagnosed earlier. However, if in the case of ARMAX-GARCH model it is accounted by choosing the function of dependence of σ_t^2 on time (through the dependence on past values of volatility and innovations), in MRS the volatility depends on the regime of the studied process when the probability of regimes changes in time (conditional variance σ_t^2 is the regime-wide sum of discrete values of unconditional variance σ_s^2 weighted by regime probability π_{ts}).

Parameters of model 6 can be estimated with different methods: maximizing the quasi-likelihood function, "Expectation-Maximization" iteration algorithm or Markov Chain Monte Carlo method. Regland and Lindström (2012) have compared these approaches and showed that the least preferred is Markov Chain Monte Carlo method while the performance of the other two methods is rather similar. Taking this into consideration, in our study we use the method of maximizing the quasi-likelihood function (for details see Hamilton 2005; Perlin 2015).

4. Results

4.1. Tweeter sentiments to exchange rate impact: baseline results

In Table 4 we report elastic net regression's results for Eq. (3). First, we can conclude that among our six control variables, oil price and index of US sanctions can potentially affect exchange rate dynamics. Negative coefficient of oil price

Table 4
Baseline elastic net regression results.

Parameters	Values of parameters
α_p	−0.207
α_r	–
α_{us}	0.087
α_{eu}	–
α_{ot}	–
α_N	–
$\beta_{LM;ew}$	−2.560
$\beta_{SWN;lw}$	−3.289
$\beta_{JR;\exp(0.5)}$	−3.450
γ_1	0.90
γ_2	0.02

Notes: We report only the coefficients identified by elastic net as different from zero.

indicates that oil price drop causes Ruble's depreciation and vice versa. Positive coefficient of US sanctions' index suggests that implementation of new US sanctions leads to the depreciation of Russian currency.

Only three of 35 indicators of Trump tweets' sentiment have significant coefficients. These are the Trump tweets' sentiment variables computed using Loughran-McDonald and SentiWordNet lexicons with equal weights and sentiment variable based on Jockers–Rinker lexicon with exponential decay scheme with decay parameter λ equaled to 0.5. The negative sign of all three coefficients indicates that negative rhetoric of Trump's tweets negatively affects Russian ruble's exchange rate causing its depreciation while positive sentiment of the tweets can cause ruble's appreciation.

Though, as it was mentioned before, the elastic net allows to select those variables, coefficients of which are potentially different from zero and the method is also resistant to multicollinearity problem, the model parameters are biased because of the regularization term which is included in the function of errors (see Eq. (4)). Besides, ordinary linear model does not count for the heteroscedasticity effect that we found in the ruble exchange rate log-return time series. To obtain unbiased estimates of the coefficients, as well as to take into account a time-dependent variance, we estimate ARMAX(0,0)-eGARCH(1,1) regression including only those control and explanatory variables for which the elastic net regression has reported coefficients different from zero (Table 4).

However, since three sentiment variables selected by elastic net reflect practically the same issue (sentiment of the Trump's tweets), we only include the variable that has shown highest level of association with the dependent variable in our preliminary estimations - Trump tweets' sentiment variable computed using Jockers–Rinker lexicon and exponential decay scheme with decay parameter λ= 0.5. Hence, the model's final specification looks as follows (see Section 3 for variables' naming convention):

$$y_t = \alpha_p p_t + \alpha_{us} d_t^{us} + \beta_{JR,\exp(0.5)} S_{t,JR,\exp(0.5)} + \sigma_t \varepsilon_t,$$

$$log\sigma_t^2 = c + (\varphi_1 \varepsilon_{t-1} + \eta_1 (|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|)) + \psi_1 log\sigma_{t-1}^2, \tag{8}$$

$$\varepsilon_t \sim t(0, \nu, \xi).$$

The estimation results of Eq. (8) are reported in Table 5.

Ljung–Box "portmanteau" test do not reveal serial correlation in the standardized residuals at 5% significance level, i.e. there is no autocorrelation in the model error. Furthermore, the squared standardized innovations are independent also at 5% significance level, i.e. the chosen GARCH specification fully catch the heteroscedasticity. Finally, the adjusted Pearson goodness-of-fit test indicates that chosen distribution form fits the residuals well at 5% significance level. Overall, we can conclude that the chosen model specification is adequate, and its coefficients' estimates allow us to make reliable conclusions.

We first discuss results for the equation of conditional variance. From Table 5 we can conclude that all coefficients of GARCH equation except constant are statistically significant at least at 5% level. There is rather strong and positive (near to one, namely, 0.868) dependence of logarithm of variation on its value in the previous moment of time. This points to the presence of pronounced effect of volatility clustering in the time-series of Russian ruble – US dollar exchange rate log-return (that is also typical for stock markets). Analysis of the coefficients of innovations and «asymmetry» component (the latter reflects the deviation of innovation absolute values from their conditional mean) and of the news impact curve (for the sake of space we do not report it here) indicates higher growth rate of volatility for positive innovations compared to negative ones. Hence, market participants are more "sensitive" to ruble depreciation than to its appreciation.

Next, we turn to the discussion of the impact of control and explanatory variables on exchange rate log-return (see Table 5). First, 1% oil price growth/drop leads to Russian ruble' appreciation/depreciation by 0.201%. Second, the implementation of the US sanctions leads to ruble's depreciation by 0.152%. Finally, toughening/softening of Trump's tweet rhetoric

Table 5
Baseline ARMAX(0,0)-eGARCH(1,1) model estimation results.

Parameters	Values of parameters
Coefficients	
α_p	−0.201*** (0.022)
α_{us}	0.152*** (0.060)
$\beta_{JR:\exp(0.5)}$	−2.078** (1.056)
c	−0.116 (0.105)
φ_1	0.122** (0.062)
ψ_1	0.868*** (0.117)
η_1	0.202** (0.081)
ξ	5.813*** (1.465)
Diagnostic	
Log-Likelihood	−456.9
AIC	1.950
BIC	2.028
HQ	1.980
Ljung-Box test, residuals (5 lags)	2.873 (0.43)
Ljung-Box test, squared residuals	2.294 (0.55)
Adj. Pearson g.o.f test, group 20	16.06 (0.65)
Adj. Pearson g.o.f test, group 50	52.54 (0.34)

Notes: 1) Significance levels: * - 10%, ** - 5%, *** - 1%; 2) Standard errors of model coefficients in parentheses for panel *Coefficients*; 3) p-value of diagnostic tests statistics in parentheses for panel *Diagnostic*.

towards Russia by 0.01 sentiment points[10] leads to ruble's depreciation/appreciation by 0.021%. The latter result confirms the study's core proposition about the impact of the US President Russia-related tweets' sentiment on Russian ruble exchange rate dynamics.

4.2. Positive and negative sentiments asymmetry

Ample research suggests asymmetry in people responses to negative versus positive information (Soroka 2006). There is evidence that negative information plays a greater role in voting/political behavior (see, e.g., Aragones 1997; Soroka and McAdams 2015) and economic/financial behavior (Afonso et al., 2012; Soroka 2006). Consequently, in this subsection, we test if negative versus positive sentiment of a tweet, computed independently from each other, affects exchange rate differently. To do this, we divided each of 5 used lexicons into two parts: words, which correspond to positive and negative sentiment, respectively. In such a manner, we get 10 lexicons, which hereafter we denote by "pos" and "neg", respectively. Next, we use the resulted 10 lexicons to compute sentiment of Trump's Russia-related tweets using the following modifications of Eq. (1):

$$S^{+}_{n,t,l} = \frac{N^{+}_{n,t,l}}{N^{+}_{n,t,l} + N^{0}_{n,t,l} + N^{-}_{n,t,l}} \tag{9}$$

$$S^{-}_{n,t,l} = \frac{N^{-}_{n,t,l}}{N^{+}_{n,t,l} + N^{0}_{n,t,l} + N^{-}_{n,t,l}}, \tag{10}$$

where Eq. (9) is used to compute tweet's n sentiment using only positive words of lexicon l and Eq. (10) - using only negative words of lexicon l. Then we use Eq. (2) above to aggregate sentiment of several tweets for seven decay schemes as in baseline model.

It is important to note that the above described approach does not divide tweets into strictly positive and negative using only the sign of $S_{n,t,l}$ (that would enable us to evaluate their effects independently from each other). Instead, we simultaneously estimate the extent of the presence of both polarities in each tweet and study their impact on the ruble exchange rate. Put that in context, this allows us to count for those tweets that have approximately the same number of positive and negative words, and, hence, exhibit almost neutral net sentiment score. We suggest that in practice, market agents might react stronger to negative rather than positive information in such tweets.

The elastic net regression results are presented in Table 6.

As can be seen from the Table 6, four sentiment variables have been chosen by elastic net. Two of them are computed with words reflecting only positive sentiment using NRC and SWN (SentiWordNet) lexicons with equal weights. The other two are computed with words reflecting only negative sentiment using LM (Loughran and McDonald) lexicon with equal weights and JR (Jockers–Rinker) lexicon with exponential decay scheme with $\lambda = 0.5$.

[10] We use the value of 0.01 because it corresponds to the typical scale of changes over time in sentiment variable (see Fig. 3 and Table 3), while the maximum value of sentiment variable magnitude is equal to 1.

Table 6
Elastic net regression results with splitted sentiment into positive and negative.

Parameters	Values of parameters
α_p	−0.205
α_r	–
α_{us}	0.086
α_{eu}	–
α_{ot}	–
α_N	–
$\beta_{NRC\_pos;ew}$	−2.034
$\beta_{SWN\_pos;ew}$	−8.964
$\beta_{LM\_neg;ew}$	−2.569
$\beta_{JR\_neg;\exp(0.5)}$	−6.670
γ_1	0.90
γ_2	0.02

Notes: We report only the coefficients identified by elastic net as different from zero.

Table 7
ARMAX(0,0)-eGARCH(1,1) model estimation results with splitted sentiment into positive and negative.

Parameters	Values of parameters
Coefficients	
α_p	−0.205*** (0.021)
α_{us}	0.151*** (0.060)
$\beta_{JR\_neg;\exp(0.5)}$	−3.275** (1.503)
$\beta_{SWN\_pos;ew}$	−2.288 (5.181)
c	−0.099 (0.095)
φ_1	0.130** (0.063)
ψ_1	0.879*** (0.108)
η_1	0.190** (0.077)
ξ	5.721*** (1.445)
Diagnostic	
Log-Likelihood	−454.5
AIC	1.943
BIC	2.031
HQ	1.978
Ljung-Box test, residuals (5 lags)	2.775 (0.45)
Ljung-Box test, squared residuals	2.273 (0.56)
Adj. Pearson g.o.f test, group 20	8.86 (0.98)
Adj. Pearson g.o.f test, group 50	46.06 (0.59)

Notes: 1) Significance levels: * - 10%, ** - 5%, *** - 1%; 2) Standard errors of model coefficients in parentheses for panel *Coefficients*; 3) p-value of diagnostic tests statistics in parentheses for panel *Diagnostic*.

As in baseline estimations, we next estimate ARMAX(0,0)-eGARCH(1,1) regression including only those variables that were chosen in elastic net regression. As pairs of the selected sentiment variables computed using words reflecting only positive or negative sentiment carry identical meaning and highly correlate with each other (bilateral correlation coefficients equal to 0.89 and 0.72 for the variables reflecting positive and negative sentiment, respectively), for each pair (of positive and negative sentiment), we only include the variable that has shown the highest level of association with our dependent variable - variable computed with words reflecting only positive sentiment using SWN (SentiWordNet) lexicon with equal weights and variable computed with words reflecting only negative sentiment using Jockers–Rinker lexicon and exponential decay scheme with decay parameter $\lambda = 0.5$:

$$y_t = \alpha_p p_t + \alpha_{us} d_t^{us} + \beta_{JR\_neg,\exp(0.5)} S_{t,JR\_neg,\exp(0.5)} + \beta_{SWN\_pos,\mathrm{ew}} S_{t,SWN\_pos,\mathrm{ew}} + \sigma_t \varepsilon_t,$$

$$log\sigma_t^2 = c + (\varphi_1 \varepsilon_{t-1} + \eta_1(|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|)) + \psi_1 log\sigma_{t-1}^2, \tag{11}$$

$$\varepsilon_t \sim t(0, \nu, \xi).$$

The results are presented in Table 7.

The coefficient of the variable reflecting positive sentiment is not statistically significant while the coefficient of the variable reflecting negative sentiment is statistically significant at 5% level with negative sign and larger absolute magnitude compared to the respective baseline result. This particularly points to the impact of negative rather than positive sentiment of Trump's rhetoric towards Russia. As for modelling of conditional variance and effects of control variables, the results are practically the same as in baseline estimations.

Table 8
Markov regime-switching model estimation results.

Parameters	Regimes	
	Economic ($s = 1$)	Political ($s = 2$)
α_p	−0.212*** (0.021)	–
α_{us}	–	0.614 (0.552)
$\beta_{JR;\exp(0.5)}$	–	−40.512*** (13.144)
σ^2	0.336*** (0.022)	2.270*** (0.716)
p_{ss}	0.98*** (0.04)	0.66*** (0.13)
T_s	62	3

Note: 1) Significance levels * - 10%, ** - 5%, *** - 1%; 2) p_{ss} is the probability of model state s is not changed from time t to time $t + 1$ and T_s is mean duration of state s (in days).

Table 9
Mean sentiment of Russia-related tweets of Donald Trump in the identified episodes of "political regime".

Period	Mean sentiment
25.01.2017–26.01.2017	0, i.e. no Russia-related tweets; see discussion in the text
19.06.2017–20.06.2017	−0.021
06.04.2018–12.04.2018	−0.067
07.08.2018–14.08.2018	−0.024
03.10.2016–31.08.2018 (the whole studied period)	*−0.011*

Notes: Mean values are reported for the sentiment variable computed using Jockers–Rinker lexicon with exponential decay scheme and parameter λ= 0.5.

4.3. Fundamental and sentiment drivers

Though in the above analysis we found statistically significant dependence of Russian ruble exchange rate on sentiment of the US president tweets, the degree of the dependence seems to be rather small. This can be due to the usage of linear models, which assess the impact of independent variables on the dependent variable as average over the studied period, that leads, in turn, to lower estimated coefficients. As was discussed in Section 2, in real life, we can expect that in some subperiods ruble exchange rate reacts more sharply to Trump's Twitter announcements (and other relevant political factors) than in the other subperiods. To verify this hypothesis and to identify subperiods of strong impact of Trump's tweets on Russian ruble exchange rate, we utilize Markov regime-switching (MRS) model as described above. Specifically, we distinguish between two regimes: $s = 1$ or "economic regime" when ruble exchange rate is explained by oil price in the world market (economic fundamental) and $s = 2$ or "political regime" when ruble exchange rate is determined by the implementation of US sanctions and sentiment of Trump's tweets (in the form of sentiment variable $S_{t,JR,\exp(0.5)}$ identified by elastic net regression, see Table 4 above). In such a manner, the model specification looks as follows:

$$y_{t,s} = \begin{cases} a_p p_t + \sigma_s \varepsilon_t, & s = 1 \\ \alpha_{us} d_t^{us} + \beta_{JR,\exp(0.5)} s_{t,JR,\exp(0.5)} + \sigma_s \varepsilon_t, & s = 2 \end{cases}. \tag{12}$$

The estimation results of Eq. (12) are reported in Table 8.

As we can see from the Table 8, in "economic regime", the estimated coefficient of oil price α_p is practically the same as in our baseline ARMAX(0,0)-eGARCH(1,1) results (see Table 5). At the same time, in "political regime", the estimated coefficient of the tweet sentiment variable has increased in absolute terms more than 19 times compared to baseline results. Its value indicates that in "political regime" toughening/softening of Trump's Twitter rhetoric towards Russia by 0.01 sentiment points leads to Ruble's depreciation/appreciation by 0.41%. Finally, the coefficient of the US sanctions index in "political regime" is not statistically significant.

4.4. Episodes of political regime: qualitative analysis

With MRS model we can further identify periods when the impact of Trump's tweets on ruble's exchange rate was significantly strong. On Fig. C1 in Appendix C, we present the graph of probability of each of two regimes in MRS model. With the threshold probability of 0.5 (or 50%), we assume that when the threshold is exceeded, exchange rate fully moves to the other regime. In such a way, we have identified four periods of "political regime": 25.01.2017–26.01.2017, 19.06.2017–20.06.2017, 06.04.2018–12.04.2018 and 07.08.2018–14.08.2018.

Donald Trump's Russia-related tweets for the identified periods of "political regime" are reported in Table D1 (see Appendix D). In Table 9 we report the mean values of sentiment variable, $S_{t,JR,\exp(\lambda=0.5)}$, for the identified episodes of "political regime".

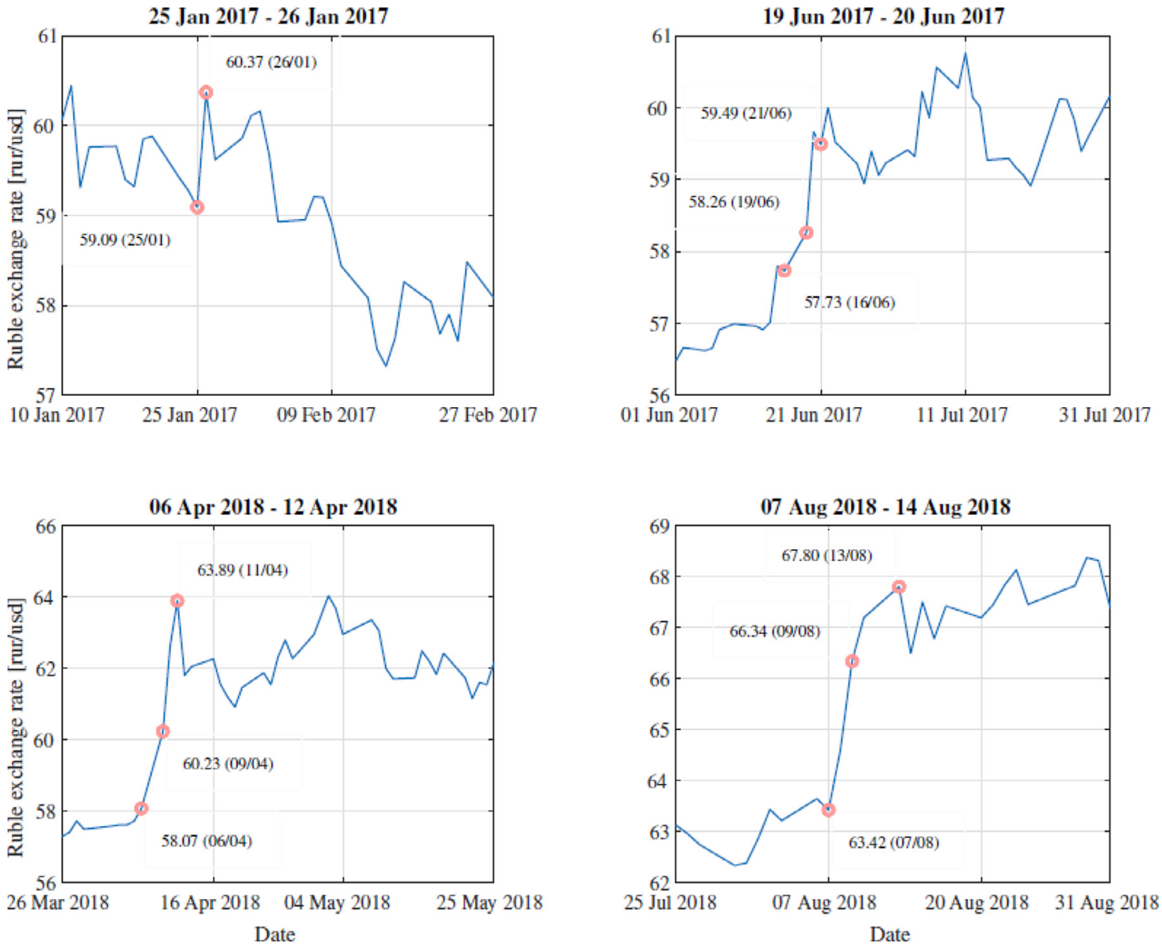


Fig. 2. Russian ruble-USD exchange rate dynamics for the episodes of "political" regime.

We can observe that for the three identified periods the magnitude of negative mean sentiment in absolute terms exceeds the magnitude of negative mean sentiment for the studied period. On Fig. 2 we also report the Russian ruble's exchange rate dynamics for the identified episodes extended by about 15 days back and 40–50 days forward.

As can be seen from Fig. 2 the ruble exchange rate's depreciation in the first identified period (25–26 of January 2017) was around 2% (computed between 25 and 26 of January 2017). However, there were no Trump's Russia-related tweets in the period of 19.01.2017–26.01.2017 (see Table 9 above) and, hence, we need to search for plausible explanation of this result. A closer look at the data revealed that on 26.01.2017 there was a rather notable oil price growth (15 times higher than average in the studied period). On the other hand, as was already noted above, the ruble has experienced a rather notable depreciation, with the speed/rate 137 times higher than average in the studied period. We further identified that in 60 days of the studied period oil price growth has been higher than average by 15 or more times. In 42 of these days (70%) ruble has appreciated as would be expected by our model (according to economic regime). In the remaining 18 days the highest depreciation rate was found on 10.04.2018 – the date belongs to the third identified political period (the description of this period is provided below). The second highest depreciation rate was found on 26.01.2017, i.e. exactly matching our first identified period. Hence, the model could not attribute this date to economic regime (because notable oil price growth was accompanied by very significant ruble depreciation) and automatically attributed it to political regime. Indeed, in rare cases, MRS model might identify states/periods incorrectly (see, e.g. Mitra and Date 2010). Therefore, careful examination of the identified periods is important.

Russian ruble's depreciation in the second identified period (19.06.2017–20.06.2017) was rather notable: around 4% if computed between 16 and 22 of June 2017. Virtually all Donald Trump's Russia-related tweets in this period (including seven preceding days) were devoted to the discussion of possible collusion between Trump and Russia (the Kremlin). Though this discussion could be considered as more related to the US domestic policy, escalation of its negative rhetoric can raise fears of new sanctions against Russia. Indeed, the Trump administration, just nine months later, on 15th of March 2018, imposed sanctions on a series of Russian organizations and individuals in retaliation for interference in the 2016 presidential election and other "malicious cyberattacks", and at that moment, this action was considered as the most significant action against Moscow since President Trump took office. In addition, the new US sanctions were indeed imposed in this period, particularly, exactly on 20th of June 2017.[11] This "coincidence" makes it somewhat difficult to attribute relatively large depreciation of Russian ruble in this period exclusively to Trump's tweets though it might be suggested that negative rhetoric of Trump's tweets was the initial signal for FX market agents about new sanctions.

Russian ruble's depreciation in the third identified period (06.04.2018–12.04.2018) was rather large: around 10% if computed between 6 and 11 of April. The media news point to the seventh tweet of the second period in Table D1 (see Appendix D). In particular, on 11th of April 2018, several renowned news agencies (Bloomberg,[12] CNBC,[13] Financial Times,[14] Newsweek[15] and Russia Today[16]) have reported that the Russian ruble hits its lowest level against the dollar since November 2016 after the tweet by President Donald Trump suggested that the U.S. was ready to launch missiles into Syria. However, this period again somewhat coincided with new US sanctions, imposed on Russia on 6th of April.[17]

Ruble depreciation in the fourth identified period (07.08.2018–14.08.2018) was also quite noticeable: around 7% if computed between 7 and 13 of August 2018. As in the second period of "political regime", all Donald Trump's Russia-related tweets in this period (including seven preceding days) were devoted to discussion of possible collusion between Trump and Russia. And again, this period coincided with the announcement of new US sanctions against Russia because of the poisoning of an ex-Russian spy (Sergei Skripal) and his daughter in the UK (BBC, 09.08.2018).[18]

Hence, all the identified periods of "political regime" - when negative sentiment of Trump's tweets has caused significant depreciation of Russian ruble - rather closely coincide with the imposition or announcement of the new US sanctions against Russia. This indicates that indeed the sentiment of Donald Trump tweets largely reflects the overall situation around Russia-USA relationship. In the studied period USA imposed new sanctions on Russia six times excluding sanctions' extension, diplomatic sanctions and sanctions against Crimea. They are summarized in Table E1 (see Appendix E). In most cases, sanctions were corporate and personal. Sanctions, imposed on 27 of August 2018 and announcement of which was related to the last identified episode of "political regime", were classified as financial.

Identified episodes of "political regime" coincide with three episodes of the new US sanctions out of six in the studied period. The analysis of the other three episodes of the US sanctions reveals rather interesting patterns. As can be seen from Table F1 in Appendix F, the first "unidentified" episode of sanctions (23.12.2016) was accompanied by only one Russia-related tweet of Donald Trump concerned with possible collusion between Russia and Trump. Though the tweet's sentiment is negative (see Table F2 in Appendix F), it is 13 times less negative than the mean sentiment of the whole studied period (see Table 9). Finally, as can be seen from the Fig. F1, this period is actually characterized by Russian ruble's appreciation.

There were no Russia-related tweets in the second "unidentified" sanctions' episode (26.01.2018). However, slight depreciation of 0.8% took place on 26.01.2018 (see Fig. F1). Finally, the third "unidentified" sanctions' episode (15.03.2018) was accompanied by three Russia-related tweets (see Table F1 in Appendix F), all associated with the discussion on possible collusion between Russia and Trump. Interestingly, their mean sentiment is positive (see Table F2 in Appendix F). This period is characterized by relatively notable depreciation of Russian ruble of around 2% if computed between 13 and 19 of March of 2018 (see Fig. F1). However, this depreciation is significantly smaller than in the three correctly identified "political regime" episodes (4, 7 and 10%).

We should note that one can suggest that the impact of rhetoric might depend on the state of vulnerability of the Russian economy, i.e. whether the rhetoric is launched in a period of rising or falling oil prices. First, our econometric approach presumes that Donald Trump's rhetoric and oil price affect Russian ruble independently from each other. Second, we carefully analyzed oil price dynamics in three identified political periods and concluded that there is no clear pattern of the dependence of Trump's rhetoric's effects for ruble on oil price dynamics.

In summary, the tentative conclusion is that those US sanctions against Russia that were accompanied by relatively large emotional coverage with negative sentiment in Donald Trump's Twitter have led to more serious negative consequences for the Russian ruble compared to those which did not have significant emotional reaction of the American president. These results might have two interpretations. The first one is that the level of seriousness of the US sanctions for Russia (in their potential negative impact for the Russian economy) and their emotional coverage (with negative sentiment) in Trump's Twitter are positively related. The second one is that market agents rather react to the emotional component associated with sanctions than to sanctions directly. Furthermore, these two interpretations might be interrelated. More specifically, as for market agents it might be rather difficult to assess potential damage of the sanctions, their judgments about this damage are based on the emotional reactions in mass media including tweets of the US President.

Finally, as two of the periods of "political regime" include exclusively tweets about possible collusion between Trump and Russia, it can be suggested that Trump's opponents, accusing him in colluding with Russia, that way make a pressure

[11] The United States imposes sanctions on 38 individuals and entities, including the military company PMC Wagner.

[12] https://www.bloomberg.com/news/articles/2018-04-11/trump-s-tweets-make-russia-s-top-export-more-valuable-than-ever

[13] https://www.cnbc.com/2018/04/11/ruble-falls-after-trump-tweet-raises-stakes-with-russia-over-syria.html

[14] https://www.ft.com/content/6744637e-3d78-11e8-b9f9-de94fa33a81e

[15] https://www.newsweek.com/trumps-moscow-missile-threat-puts-russias-rouble-track-worst-week-decades-881239

[16] https://www.rt.com/business/423910-trump-trolling-russia-stocks/

[17] The United States designates 38 Russian businessmen for visa bans and asset freezes to punish Russian "malign activity" worldwide.

[18] However, these sanctions were officially imposed only on 27 of August. The United States imposed a ban on arms sales, arms-sales financing, U.S. government credit or other financial assistance, exports of national-security-sensitive goods, and most foreign assistance to Russia under the terms of the Chemical and Biological Weapons Control and Elimination Act.

on him to impose new sanctions against Russia. Therefore, such tweets increase the fears of market agents about the future of Russia (and signal about new sanctions) which causes depreciation of Russia's currency.

4.5. Robustness checking

It can be suggested that Donald Trump's Russia-related tweets affect not only Russian currency but all other currencies as their negative sentiment might indicate the possibility of World War III, for example, or significant worsening of the political climate in the World in general. Then our results might reflect these issues rather than being Russia-specific. To test this, we also estimated elastic net regressions with computed 35 sentiment variables (the same as in baseline estimations, i.e. computed based on Donald Trump Russia-related tweets) for exchange rates of other major currencies (EURO-USD, GBP-USD, JPY-USD and CHY-USD). Though for EURO-USD, JPY-USD and CHY-USD exchange rates one sentiment variable was selected by elastic net, in respective ARMAX-GARCH model none of them was statistically significant (on 10% level).

We further performed factor analysis for 35 sentiment variables and found that only the first principal component (which explains 63% of variance) was statistically significant (at 10% significance level) with expected sign in the ARMAX-GARCH model for ruble's exchange rate with oil price, US sanction index and included sequentially six first principal components as explanatory variables. Hence, in general, this alternative method of dealing with many correlated explanatory variables gives similar results as elastic net approach used in this study.

5. Conclusions

In this paper we investigated the effects of the sentiment of Donald Trump's Russia-related tweets on the exchange rate of Russian ruble. Using several econometric techniques, including elastic net regression, ARMAX-GARCH and Markov regime-switching models, we concluded that Trump's tweets' sentiment, particularly negative, indeed affects Russian ruble's exchange rate's dynamics. However, this impact is episodic and short term. More specifically, in certain short (around 3 days) periods (which are few) Trump's Twitter rhetoric with negative sentiment towards Russia causes Russian currency's sharp depreciation. Furthermore, Markov regime-switching approach allowed us to reveal that these periods coincide with the implementation or announcement of new US sanctions. This points to a broader conclusion that Western sanctions indeed have negative effects on the Russian economy. Finally, our analysis shows that those US sanctions that were not accompanied by negative tweets of the US president, did not affect Russian ruble. This finding pinpoints the role of emotions in economic decisions.

The contributions of this paper are several. First, we present a framework that enables to rather precisely estimate the impact of the sentiment of social media messages of an influential individual on exchange rate dynamics. Second, we advance sentiment analysis by using multiple lexicons' approach to evaluate the sentiment of text messages. Third, we present an empirical analysis of the impact of the US president tweets on Russian ruble's exchange rate.

Our paper has implications for both empirical and theoretical literature in macroeconomics and development. On the empirical side, we point to the importance of using regime-switching approach when evaluating the impact of information arrival and its sentiment on exchange rate dynamics. Our findings suggest that at least for certain types of information this impact can be episodic and short-term and, hence, might not be captured in a proper way by models without regime-switching.

Our paper has some implications also for theoretical literature. More specifically, our results suggest that it might be important to explicitly count for the emotional component of policy factors in macroeconomic modelling of exchange rates, particularly in emerging markets.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2021.02.002.

Appendix A

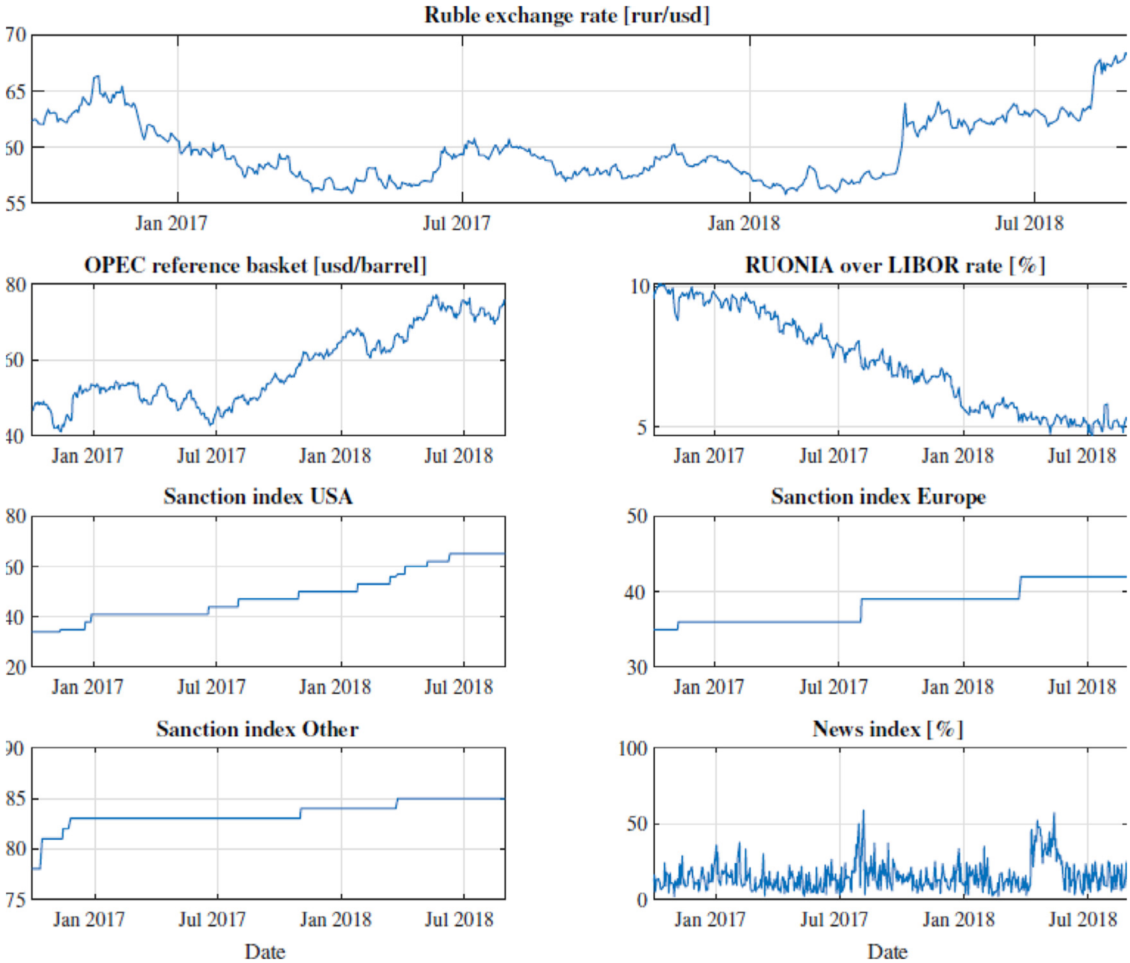

Fig. A1. Dependent and control variables for the period from 03.10.2016 to 31.08.2018.

Appendix B

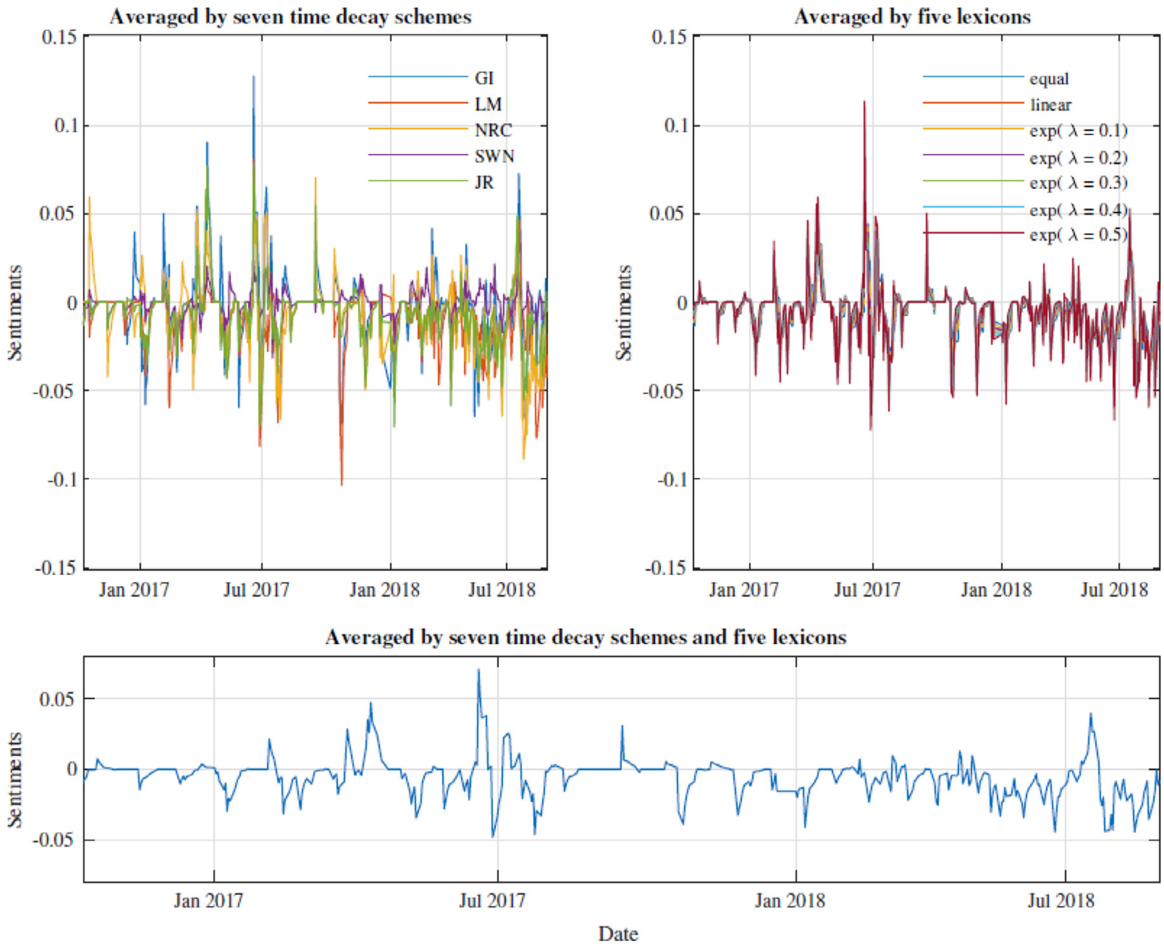

Fig. B1. Donald Trump's Russia-related tweets' sentiment patterns.

Appendix C

Appendix C contains graphical presentation of MRS model's regimes

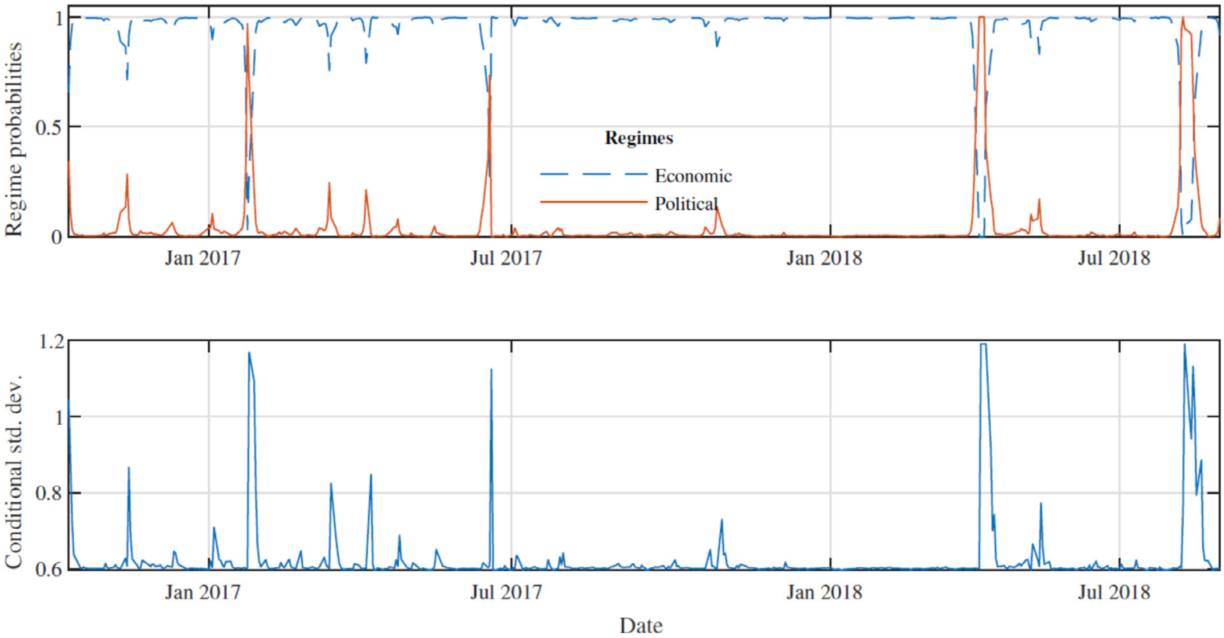

Fig. C1. The probability of "economic" (dashed line) and "political" (solid line) regimes according to MRS model (upper panel) and the corresponding dynamics of conditional standard deviation of Russian ruble exchange rate log-return (lower panel).

Appendix D

Table D1
Donald Trump's Russia-related tweets for episodes of "political regime" with state probability above 0.5 (including one week before).

N	Tweet text	Created at (GMT)
19.06.2017–20.06.2017		
1	RT @foxandfriends: "Yesterday's hearings provided zero evidence of collusion between our campaign and the Russians because there wasn't any...	2017–06–12 02:07:30
2	They made up a phony collusion with the Russians story, found zero proof, so now they go for obstruction of justice on the phony story. Nice	2017–06–15 10:55:37
3	Why is that Hillary Clintons family and Dems dealings with Russia are not looked at, but my non-dealings are?	2017–06–15 19:43:31
4	After 7 months of investigations \ committee hearings about my "collusion with the Russians," nobody has been able to show any proof. Sad!	2017–06–16 11:53:56
5	RT @DiamondandSilk: The Media Says: The President Should Stop Tweeting about Russia. Well, Why Don't the Media Take Their Own Advice \ S...	2017–06–18 21:07:12
06.04.2018–12.04.2018		
1	Many dead, including women and children, in mindless CHEMICAL attack in Syria. Area of atrocity is in lockdown and encircled by Syrian Army, making it completely inaccessible to outside world. President Putin, Russia and Iran are responsible for backing Animal Assad. Big price...	2018–04–08 13:00:06
2	If President Obama had crossed his stated Red Line In The Sand, the Syrian disaster would have ended long ago! Animal Assad would have been history!	2018–04–08 13:12:57
3	RT @StateDept: .@POTUS Trump condemns the heinous attack on innocent Syrians with banned chemical weapons. \#Syria https://t.co/qiEahlL3Ah	2018–04–09 16:55:41
4	The Failing New York Times wrote another phony story. It was political pundit Doug Schoen, not a Ukrainian businessman, who asked me to do a short speech by phone (Skype), hosted by Doug, in Ukraine. I was very positive about Ukraine-another negative to the Fake Russia C story!	2018–04–11 10:30:19
5	So much Fake News about what is going on in the White House. Very calm and calculated with a big focus on open and fair trade with China, the coming North Korea meeting and, of course, the vicious gas attack in Syria. Feels great to have Bolton \Larry K on board. I (we) are	2018–04–11 10:38:42

(*continued on next page*)

Table D1 (*continued*)

N	Tweet text	Created at (GMT)
6	....doing things that nobody thought possible, despite the never ending and corrupt Russia Investigation, which takes tremendous time and focus. No Collusion or Obstruction (other than I fight back), so now they do the Unthinkable, and RAID a lawyers office for information! BAD!	2018–04–11 10:47:37
7	Russia vows to shoot down any and all missiles fired at Syria. Get ready Russia, because they will be coming, nice and new and "smart!" You shouldn't be partners with a Gas Killing Animal who kills his people and enjoys it!	2018–04–11 10:57:30
8	Our relationship with Russia is worse now than it has ever been, and that includes the Cold War. There is no reason for this. Russia needs us to help with their economy, something that would be very easy to do, and we need all nations to work together. Stop the arms race?	2018–04–11 11:37:56
9	Much of the bad blood with Russia is caused by the Fake \Corrupt Russia Investigation, headed up by the all Democrat loyalists, or people that worked for Obama. Mueller is most conflicted of all (except Rosenstein who signed FISA \ Comey letter). No Collusion, so they go crazy!	2018–04–11 13:00:23
10	Never said when an attack on Syria would take place. Could be very soon or not so soon at all! In any event, the United States, under my Administration, has done a great job of ridding the region of ISIS. Where is our "Thank you America?"	2018–04–12 10:15:25
07.08.2018–14.08.2018		
1	Russian Collusion with the Trump Campaign, one of the most successful in history, is a TOTAL HOAX. The Democrats paid for the phony and discredited Dossier which was, along with Comey, McCabe, Strzok and his lover, the lovely Lisa Page, used to begin the Witch Hunt. Disgraceful!	2018–08–01 14:01:53 \\
2	"We already have a smocking gun about a campaign getting dirt on their opponent, it was Hillary Clinton. How is it OK for Hillary Clinton to proactively seek dirt from the Russians but the Trump campaign met at the Russians request and that is bad?" Marc Thiessen, Washington Post	2018–08–01 15:23:13
3	Looking back on history, who was treated worse, Alfonse Capone, legendary mob boss, killer and "Public Enemy Number One," or Paul Manafort, political operative \ Reagan/Dole darling, now serving solitary confinement - although convicted of nothing? Where is the Russian Collusion?	2018–08–01 15:35:47
4	"We already have a smoking gun about a campaign getting dirt on their opponent, it was Hillary Clinton. How is it OK for Hillary Clinton to proactively seek dirt from the Russians but the Trump campaign met at the Russians request and that is bad?" Marc Thiessen, Washington Post	2018–08–01 15:56:31
5	Congratulations to @GreggJarrett on The TREMENDOUS success of his just out book, "The Russia Hoax, The Illicit Scheme To Clear Hillary Clinton \ Frame Donald Trump." Already number one on Amazon. Hard work from a brilliant guy. It's the Real Story of the Rigged Witch Hunt!	2018–08–02 04:38:15
6	Congratulations to Gregg Jarrett on his book, "THE RUSSIA HOAX, THE ILLICIT SCHEME TO CLEAR HILLARY CLINTON AND FRAME DONALD TRUMP," going to \#1 on @nytimes and Amazon. It is indeed a HOAX and WITCH HUNT, illegally started by people who have already been disgraced. Great book!	2018–08–04 03:01:46
7	…Dianne is the person leading our Nation on "Collusion" with Russia (only done by Dems). Will she now investigate herself? https://t.co/OG6l04bBwg	2018–08–04 03:28:06
8	"Collusion with Russia was very real. Hillary Clinton and her team 100\% colluded with the Russians, and so did Adam Schiff who is on tape trying to collude with what he thought was Russians to obtain compromising material on DJT. We also know that Hillary Clinton paid through....	2018–08–06 14:13:10
9	....a law firm, eventually Kremlin connected sources, to gather info on Donald Trump. Collusion is very real with Russia, but only with Hillary and the Democrats, and we should demand a full investigation." Dan Bongino on @foxandfriends Looking forward to the new IG Report!	2018–08–06 14:25:56
10	The Iran sanctions have officially been cast. These are the most biting sanctions ever imposed, and in November they ratchet up to yet another level. Anyone doing business with Iran will NOT be doing business with the United States. I am asking for WORLD PEACE, nothing less!	2018–08–07 09:31:46
11	"There has been no evidence whatsoever that Donald Trump or the campaign was involved in any kind of collusion to fix the 2016 election. In fact the evidence is the opposite, that Hillary Clinton \ the Democrats colluded with the Russians to fix the 2016 election." @GrahamLedger	2018–08–09 13:22:39
12	.@MariaBartiromo "No evidence to launch even an investigation into potential collusion between Donald Trump and the Russians - and here we are, a year and a half later."	2018–08–10 11:49:48
13	Fired FBI Agent Peter Strzok is a fraud, as is the rigged investigation he started. There was no Collusion or Obstruction with Russia, and everybody, including the Democrats, know it. The only Collusion and Obstruction was by Crooked Hillary, the Democrats and the DNC!	2018–08–14 13:01:50

Appendix E

Table E1
The US sanctions against Russia in the studied period excluding sanctions' extensions, sanctions against Crimea and diplomatic sanctions.

Date	Sanctions	Reason	Type	Episode of "sentiment regime"
23 December 2016	The United States designates 23 Russian companies for sanctions.	Ukraine	Corporate	No
20 June 2017	The United States imposes sanctions on 38 individuals and entities, including the military company PMC Wagner.	Ukraine	Personal, Corporate	Yes, 19–20 June 2017
26 January 2018	The United States imposes sanctions on 21 individuals and nine companies.	Ukraine	Corporate, Personal	No
15 March 2018	The United States makes first use of CATSAA law to impose sanctions on 19 Russians, including 13 indicted in Robert Mueller's investigation into Moscow's alleged meddling in the 2016 presidential election and Internet Research LLC, commonly known as the Russian "troll factory".	Elections	Personal, Corporate	No
6 April 2018	The United States designates 38 Russian businessmen for visa bans and asset freezes to punish Russian "malign activity" worldwide.	Syria	Personal	Yes, 06–12 April 2018
27 August 2018	The United States imposes a ban on arms sales, arms-sales financing, U.S. government credit or other financial assistance, exports of national-security-sensitive goods, and most foreign assistance to Russia under the terms of the Chemical and Biological Weapons Control and Elimination Act.	Skripal	Financial	Yes, 07–14 August 2018 (were announced on 10 of August)

Source: https://www.rferl.org/a/russia-sanctions-timeline/29/477/179.html.

Appendix F

Table F1
Donald Trump's Russia-related tweets for the US sanctions' episodes of non "political regime".

N	Tweet text	Created at (GMT)
23.12.2016		
1	If Russia, or some other entity, was hacking, why did the White House wait so long to act? Why did they only complain after Hillary lost?	2016–12–15 14:24:29
26.01.2018 There is no tweets		
15.03.2018		
1	The Failing New York Times purposely wrote a false story stating that I am unhappy with my legal team on the Russia case and am going to add another lawyer to help out. Wrong. I am VERY happy with my lawyers, John Dowd, Ty Cobb and Jay Sekulow. They are doing a great job and.....	2018–03–11 13:41:04
2	...have shown conclusively that there was no Collusion with Russia..just excuse for losing. The only Collusion was that done by the DNC, the Democrats and Crooked Hillary. The writer of the story, Maggie Haberman, a Hillary flunky, knows nothing about me and is not given access.	2018–03–11 13:50:47
3	THE HOUSE INTELLIGENCE COMMITTEE HAS, AFTER A 14 MONTH LONG IN-DEPTH INVESTIGATION, FOUND NO EVIDENCE OF COLLUSION OR COORDINATION BETWEEN THE TRUMP CAMPAIGN AND RUSSIA TO INFLUENCE THE 2016 PRESIDENTIAL ELECTION.	2018–03–13 00:49:27

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Table F2
Mean sentiment of Russia-related tweets of Donald Trump in the US sanctions' episodes of non "political regime".

Period	Mean sentiment
23.12.2016	−0.0005
26.1.2018	0.0000
15.3.2018	0.0015

Notes: Mean values are reported for the sentiment variable computed using Jockers–Rinker lexicon with exponential decay scheme and parameter $\lambda = 0.5$.

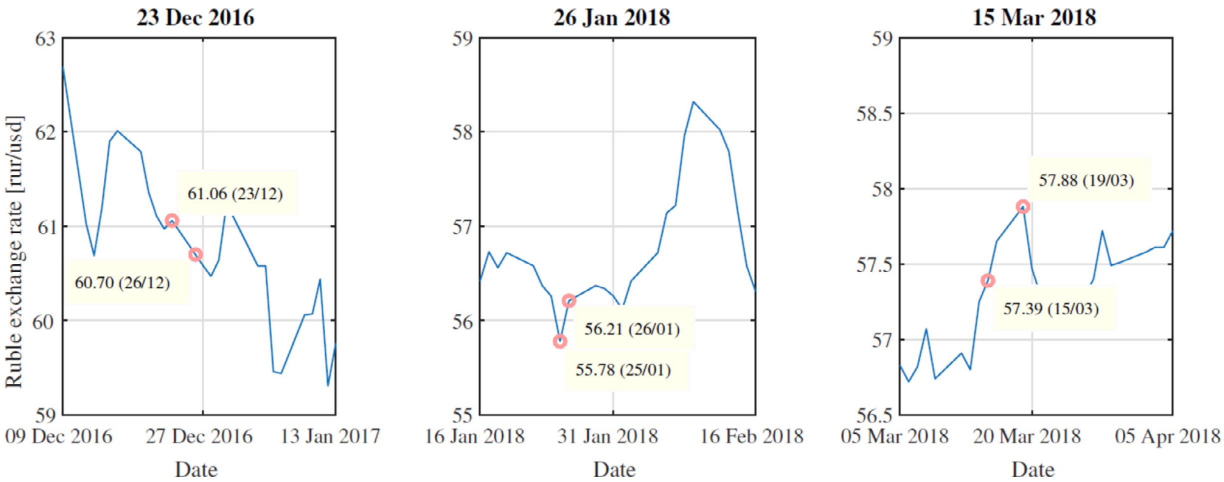

Fig. F1. Russian ruble-USD exchange rate dynamics for the US sanctions' episodes of non "political regime".

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