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The Role of Country-pair-related News Sentiment in Foreign Exchange

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This article explores the relative, explanatory contribution of country-pair-related political and financial news to foreign exchange rates. Contributing political factors are measured through the sentiment scores of published news while contributing financial factors are measured through various economic indicators such as price and volume of USD and CNY oil futures, the Russian IMOEX Index, and corresponding interest differentials. The results show that news sentiment plays a minor role in exchange rate determination while other factors such as prices and traded volumes in oil future contracts and interest differentials are significant contributing factors to the exchange rate determination. Nevertheless, the quality and quantity of news coverage of geo-political or economic events seems to play an important role when it comes to the impact of news on exchange rates. Among the sentiment-analyzed currency pairs, EUR/USD exhibits by far the highest sensitivity to political and economic news, followed by EUR/RUB, RUB/CNY, EUR/CNY, USD/CNY, and USD/RUB.

Keywords: *foreign exchange, news sentiment analysis, text mining, geo-political sentiment*

JEL-Codes: *F31, E71*

Introduction

As international trade relationships differ very often from political relationships, the geo-political and economic events and developments which are being reported in the news, it is very hard to assign one score which measures the status of the relationship between two countries. Even though political and economic factors are heavily intertwined, the focus and main contribution of this paper is the investigation of the role of news and media in the exchange rate development. For this purpose an appropriate measure to quantify the relationship between two countries needs to be developed. One way to measure the relationship between two countries is to measure the sentiment score of reported news associated with this country pair. The relationship status of two countries can be subsumed under one numeraire, the sentiment score, in order to reflect the developments in the economic as well as political spheres.

Geo-political developments are often the main driver of exchange rate fluctuations which then utilize financial markets as instruments to achieve its political goals. In other cases, geo-political developments are a result of movements in the financial markets. In general, the interaction between political

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decisions and financial market is reciprocal. The reaction of one party is a time-lagged function of the other party. For example, an increase in consumer prices might be due to the political decision to print more money in order to finance high debt levels. The high debt levels might be a reflection of negative trade balances with other countries with who the country of origin might sustain good relations. The country of origin thus, chose through a political decision by instumentalizing the financial markets to sustain a certain economic condition through the imposition of a certain trade relationship. This relationship will most likely exhibit in general a positive sentiment.

If for certain reasons, e.g., financial reasons, economic conditions in the partner country deteriorate, and the partner country politically decides to scale back exports, this would indeed negatively affect the country of origin and thus, be reflected in the country pair's sentiment. It would be hard to trace back the causality for this negative sentiment change as it is unclear if this sentiment change should be catergorized as a political or economic reason. However, the political decision, respectively financial markets reaction will be measurable through news by calculating the sentiment score of the corresponding news article. Furthermore, the political decision will be reflected in the movements of the financial markets, which can again be measured. There are certain economic factors, e.g., trade-related indicators, which reveal the status of a relationship between two countries. A very suitable indicator to measure the financial relationship between two countries are foreign exchange rates since they subsume political as well as economic differences between two countries.

Economic factors which determine the exchange rates, such as trade relationships and interest rate differentials could also be categorized as political decisions as it is up to the political and governing decision body to set up and maintain consensual agreements or set the cost of money in their country. By setting the interest rates in their own country, governments can implicitly change the sentiment relationship towards a partner country since the interest differential influences the exchange rates. This can make exports or imports for the partner country cheaper or more expensive, and thus, also influence politically the situation in the partner country.

Political attitude towards a partner country can look differently though, than the economic relationship. A very good example for a diverging relationship between political and economic sentiment between two countries or regions is the relationship between the European Union and Russia. While maintaining a distorted but still functioning economic relationship with Russia, as reflected by the constant agreements on EU gas imports from Russia over decades, the political relationship has been rather shuttered as the EU has been imposing sanctions on Russia over the same time period.

Another factor that plays an important role is the relative divergence of sentiment in different time dimensions. Long-term country relationships might differ from short term country relationships, even though they might be highly auto-correlated with expansion of time. The reason for an increasing auto-correlation might be attributed to the characteristics that the long-term development of the sentiment between two countries is a function of short-term developments.

However, the time threshold at which short-term sentiment coincides with long-term sentiment is unknown. A convergence may even never occur, which makes the time-dependent perspective of sentiment valuation a paradoxon. The reason for this behavior might be due to separation of economic and political interests. Divergent interests of acting partners within a country may determine different policies and therefore cause short-term sentiment developments diverge from long-term sentiment values. Nevertheless, to find out if or when a convergence of the time-dependent sentiment differential occurs is subject to further research. The ultimate flip, respectively convergence of a sentiment differential may occur when some trigger event happens, resources are exhausted, or agreements are reached or breached.

Literature Review

Sentiment analysis has been widely adapted in foreign exchange forecasting and a vast amount of research has been conducted in order to understand the power of news on financial markets.

This article focuses on the purely marginal contribution of news media on geo-political and economic events and developments on the foreign exchange rates. The difference to existing literature is the focus on country-pair related sentiment scores and their correspondence and investigation of their explanatory power on the corresponding exchange rate, which hasn't been considered in the literature yet. While most of the literature analyzes non-systematically news, social media postings or tweets, they don't relate the calculated sentiments scores to corresponding country-pairs. That's the novelty of this research paper. Moreover, a lot of research works on a high-frequency time scale, the focus of this paper is to analyze the contribution of news sentiment on the FX rate movements on a daily basis besides other, market determining factors. By using end-of-day closing prices we filter automatically intraday noise and allow at the same time other market-determining factors to take effect which allows to extract the net-effect of sentiment scoring on the FX rates.

Considering the utilization of social media platforms, such as Twitter, Zhao et al. (2022) gather network social media data in order to predict foreign exchange rates generated during the new round of trade war between China and the United States. They use a nonlinear model LSTM based on machine learning is used to model and predict the high-frequency exchange rate sequence. They show that the accuracy of the exchange rate forecasting model with the sentiment factors of public opinion is improved.

Komariah et al. (2016) perform a study on efficient market hypothesis to predict exchange rate trends using sentiment analysis of Twitter data. They take daily Twitter sentiments using the hybrid approach of the lexicon-based approach and the naive Bayes classifier to analyze the currency exchange rate movement of Indonesia Rupiah vs US dollar as a way of testing the Efficient Market Hypothesis. They find that public information provided by Twitter sentiment correlates with changes in the exchange market trends.

Also Plakandaras et al. (2015) find evidence for the violation of the efficient market hypothesis by utilization of sentiment data. They take investors' sentiment on a given exchange rate as a possible predictor of its future evolution. As a proxy of investors' sentiment they use StockTwits posts, a message board dedicated to finance. Their empirical findings reject the Efficient Market Hypothesis even in its weak form for all four exchange rates. They find evidence that investors' sentiment as expressed in public message boards can be an additional source of information regarding the future directional movement of the exchange rates to the ones proposed by economic theory.

Most of the literature concerns the sentiment analysis of stock prices. There exists a vast amount of research dealing with the predictive power of news in stock prices. Even though stock prices are not the subject of this research here, the predictive power of sentiment analysis in financial markets can be stressed. Chowdhury et al. (2014) apply a predictive model to predict sentiment around stock prices. Their results result shows an average accuracy score for identifying correct sentiment of around 70.1%. The comparison between positive sentiment curve and stock price trends reveals 67% co-relation between them, which indicates towards existence of a semi-strong to strong efficient market hypothesis.

In latest developments, the relationship between news sentiments and new asset classes such as crypto currencies is being increasingly subject to research. Georgoula et al. (2015) use time-series and sentiment analysis to analyze the relationship between Bitcoin prices and fundamental economic variables, technological factors and measurements of collective mood derived from Twitter feeds. They conduct a series of short-run regressions which show that the Twitter sentiment ratio is positively correlated with Bitcoin prices while the value of Bitcoins is negatively affected by the exchange rate between the USD and the Euro. Rognone et al. (2020) use high frequency intra-day data to investigate the influence of unscheduled currency and Bitcoin news on the returns, volume and volatility of the cryptocurrency Bitcoin and traditional currencies over the period from January 2012 to November 2018. They find that unlike traditional currencies, Bitcoin reacts positively to both positive and negative news.

Xing et al. (2020) also analyze news sentiment in a high-frequency context of the foreign exchange market. Their model outperforms alternative sentiment analysis approaches and confirms that news sentiment alone may have predictive power for Forex price movements.

In a very direct-politics-related research, Colonescu (2018) analyzes the effects of Donald Trump's tweets on U.S. financial and foreign exchange markets. He finds a correlation between various moving average window lengths of tweet content and the DJI index. Some short term and lasting effects are also detected on U.S. -Canada and U.S. composite exchange rates.

Lee et al. (2019) perform a currency exchange rate prediction with long short-term memory networks based on attention and news sentiment analysis. They use the Australian dollar (AUD) against the U.S. dollar (USD) as a case study and study the prediction AUD rate for next day, week, two-week, and month. Their results show that adding sentiment score of the news articles and matching keywords of "up/increase" can reduce prediction error by at least 15%.

Chethan and Sangeetha (2020) take available tweets on social media about USD/INR exchange rate, BSE Sensex, NSE Nifty and calculate a sentiment score for each of the sentences where any twitter feeds using the keywords: USD/INR, #USD/INR, #BSE, #Sensex, #NSE are mentioned. They show that Sentiment analysis can be used effectively by investors to make a prediction of what direction the price will realize based on the sentiment prevailing in the market. They only classify sentiment into positive, negative, or neutral, whereas the model used in this article here calculates a sentiment score between -1 and +1 by utilization of the tanh function. Details on the sentiment calculation can be found in Shukla and Unger (2022).

Data and Methodology

The directional causality of the political and financial determinants of the FX rate is not subject of this article but could be subject to further research. What we are interested in this paper is to test empirically to which extent news on geo-political and economic developments translate into the exchange rate between two countries. For this purpose the news sentiments of several exchange rate pairs, representing country or regional pairs, are being calculated. Then, the corresponding country or region pair exchange rate is regressed on several independent variables such as the calculated sentiment score, the price and volume of the corresponding oil or stock market index future, as well as the corresponding interest differential. The main countries or regions which also exhibit the most important and impactful news are USA, European Union, Russia, and China. The corresponding currency pairs of interest are all combinations of all cross-country pairs: EUR/USD, EUR/RUB, RUB/CNY, EUR/CNY, USD/CNY, and USD/RUB.

The data we use for measuring geo-political news is being retrieved from google news and calculated by using an own model for sentiment analysis. Through utilization of a web-scraper we perform high-performance text mining using latest, state-of the art machine learning tools which are capable of identifying relevant news articles, screening of these news articles, identifying relevant keywords and associations with country names, respectively relevant country pairs, and calculation of a sentiment score for the associated country pairs.

The underlying learning model is BERT (Bidirectional Encoder Representations from Transformers) which is also used by the google search engine. (Alammar 2019) For the named entity recognition (NER), which can identify person, location, and organization from a news and relate it to a country, a deep learning model Peters et al. (2018) is used. For further details the reader might refer to the article by Shukla and Unger (2022).

The time-horizon we use is as long as free google news archive allows to retrieve and download news backwards, which is usually not longer than 5-9 months. The most accumulated news is usually available in the recent history, i.e., last couple of weeks.

The financial data we use are being retrieved from Bloomberg. The following data and time frames are used correspondingly for exchange rates and news sentiment, Sent: EUR/USD (07/16/2021-05/23/2022), EUR/RUB (12/09/2021-05/23/2022), RUB/CNY (11/25/2021-05/23/2022), EUR/CNY (09/08/2021-05/23/2022), USD/CNY (08/12/2021-05/23/2022), USD/RUB (01/28/2022-05/23/2022).

For the same corresponding time frames the following financial indices for each currency pair are used: Price and volume Brent crude oil future contracts (Brent_p, Brent_v), price and volume WTI crude oil future contracts (WTI_p, WTI_v), Russia stock market index price and volume (IMOEX_p, IMOEX_v), oil price and volume Shanghai crude oil future contracts (SCPA_p, SCPA_v), EUR/USD 1y forward rate (EURUSD_Fwd), EUR/RUB 1y forward rate (EURRUB_Fwd), RUB/CNY 1y forward rate (RUBCNY_Fwd), EUR/CNY 1y forward rate (EURCNY_Fwd), USD/RUB 1y forward rate (USDRUB_Fwd), USD/CNY 1y forward rate (USDCNY_Fwd).

The forward rate premium is being calculated following the standard formula to calculate the interest rate differential:

$$p = \frac{1+i_f}{1+i_h} - 1, \tag{1}$$

where p is the 1 year forward rate premium, i_f is the 1 year interest rate of the foreign currency, and i_h is the 1 year interest rate of the home currency. The first denominated currency in the exchange rate is considered to be the home currency, e.g., in case of EUR/USD, EUR would be the home currency, and USD would be the foreign currency.

The following interest rates were used for the corresponding currencies:

EUR: 12m EURIBOR, USD: 12m USD-LIBOR, RUB: Bank of Russia key rate, CNY: China 1y lending rates.

The dates used for the analysis are contingent on the available news sentiment score on the particular day. Not every country pair or associated representations, like head politicians, are mentioned every day in the news. Besides that, due to the limitation of freely available news sources in the google archives, more weight is being put on recent news than older news. This causes a rather fragmented time series where certain dates within the above-mentioned time frames are not available and thus, cause gaps. Nevertheless, the available data points give an indication where the sentiment score moved, e.g., within several weeks. The analyzed time series of the currency pairs are therefore of different length.

The Models

The multiple regressions used for each currency pairs are the following:

$$USDRUB = \alpha + \beta_1 Sent_{USDRUB} + \beta_2 WTI_p + \beta_3 WTI_v + \beta_4 IMOEX_p + \beta_5 IMOEX_v + \beta_6 USDRUB_{Fwd} + \epsilon_i, \tag{2}$$

$$USDCNY = \alpha + \beta_1 Sent_{USDCNY} + \beta_2 WTI_p + \beta_3 WTI_v + \beta_4 SCPA_p + \beta_5 SCPA_v + \beta_6 USDCNY_{Fwd} + \epsilon_i, \tag{3}$$

$$EURUSD = \alpha + \beta_1 Sent_{EURUSD} + \beta_2 Brent_p + \beta_3 Brent_v + \beta_4 WTI_p + \beta_5 WTI_v + \beta_6 EURUSD_{Fwd} + \epsilon_i, \tag{4}$$

$$EURRUB = \alpha + \beta_1 Sent_{EURRUB} + \beta_2 WTI_p + \beta_3 WTI_v + \beta_4 Brent_p + \beta_5 Brent_v + \beta_6 IMOEX_p + \beta_7 IMOEX_v + \beta_8 EURRUB_{Fwd} + \epsilon_i, \quad (5)$$

$$RUBCNY = \alpha + \beta_1 Sent_{RUBCNY} + \beta_2 IMOEX_p + \beta_3 IMOEX_v + \beta_4 SCPA_p + \beta_5 SCPA_v + \beta_6 Brent_p + \beta_7 Brent_v + \beta_8 RUBCNY_{Fwd} + \epsilon_i, \quad (6)$$

$$EURCNY = \alpha + \beta_1 Sent_{EURCNY} + \beta_2 SCPA_p + \beta_3 SCPA_v + \beta_4 Brent_p + \beta_5 Brent_v + \beta_6 WTI_p + \beta_7 WTI_v + \beta_8 EURCNY_{Fwd} + \epsilon_i. \quad (7)$$

By regressing the exchange rates on the news sentiment score as well as on the corresponding financial indicators it is possible to determine the influencing capability of each regressor. Our particular interest lies in the explanatory power of the sentiment score, or in other words, in the influencing capability of news to have an impact on exchange rates.

Results

Table 1. *Estimation Results of USDRUB*

USDRUB	**Coefficients**	**P-value**
Intercept	48.8381	0.1949
Sent_USDRUB	0.4060	0.9734
WTI_p	-0.0547	0.8278
WTI_v	0.0000	0.8432
IMOEX_p	0.0019	0.7067
IMOEX_v	0.0000	0.1615
USDRUB_Fwd	615.6902	4.93E-07

Table 2. *Estimation Results of USDCNY*

EURUSD	**Coefficients**	**P-value**
Intercept	1.2185	3.62E-08
Sent_EURUSD	-0.0167	0.1923
Brent_p	0.0052	0.2509
Brent_v	-1.021E-07	0.0266
WTI_p	-0.0062	0.1318
WTI_v	1.865E-07	0.0089
EURUSD_Fwd	-4.9207	0.2129

Table 3. *Estimation Results of EURUSD*

USDCNY	**Coefficients**	**P-value**
Intercept	5.6375	2.43E-09
Sent_USDCNY	0.0060	0.9049
WTI_p	0.0036	0.5391
WTI_v	-2.219E-07	0.0015
SCPA_p	0.0009	0.4289
SCPA_v	5.8095E-07	0.1492
USDCNE_Fwd	7.6922	0.3526

Table 4. *Estimation Results of EURRUB*

EURRUB	Coefficients	P-value
Intercept	-116.3777	0.0404
Sent_EURRUB	2.6483	0.6753
WTI_p	-3.2035	0.0201
WTI_v	-6.489E-06	0.7195
Brent_p	4.1033	0.0072
Brent_v	1.9345E-05	0.2681
IMOEX_p	0.0217	0.0148
IMOEX_v	-1.363E-11	0.5861
EURRUB_Fwd	198.2203	1.97E-05

Table 5. *Estimation Results of RUBCNY*

RUBCNY	Coefficients	P-value
Intercept	0.0860	0.2986
Sent_RUBCNY	0.0015	0.6779
IMOEX_p	-6.38796E-06	0.5867
IMOEX_v	-8.90655E-14	0.0050
SCPA_p	0.0001	0.1122
SCPA_v	6.47239E-08	0.0239
Brent_p	0.0003	0.6133
Brent_v	-2.76817E-08	0.0013
RUBCNY_Fwd	8.3755	0.1154

Table 6. *Estimation Results of EURCNY*

EURCNY	Coefficients	P-value
Intercept	8.8392	1.36E-13
Sent_EURCNY	-0.0156	0.7302
SCPA_p	-0.0019	0.2193
SCPA_v	-5.31726E-07	0.0987
Brent_p	-0.0189	0.1512
Brent_v	-1.31873E-07	0.4672
WTI_p	0.0164	0.1600
WTI_v	1.11999E-07	0.4973
EURCNY_Fwd	-2.6311	0.4241

Summary Statistics

Table 7. *Currency Pair Statistics*

Currency	Corr	p-value
EURUSD	-0.28388	0.192312
EURRUB	-0.09167	0.67526
RUBCNY	0.152867	0.677922
EURCNY	-0.19559	0.730206
USDCNY	0.179593	0.90489
USDRUB	-0.20627	0.973429

Tables 1-6 report the estimation results of all currency pairs regressed on the financial indicators.

Table 1 provides the estimation statistics of the aggregated U.S. - and Russian-related news sentiment score and related financial indicators used as parameters to explain the USD/RUB exchange rate. We can see that the only factor that exhibits a significant explanatory power at a 95% confidence level is the interest differential, measured through the USD/RUB forward rate premium. The U.S. -and Russian-related news sentiment score does not exhibit any significant explanatory power to explain the USD/RUB exchange rate.

Table 2 presents the estimation statistics of the aggregated U.S. - and Chinese-related news sentiment score and related financial indicators used as parameters to explain the USD/CNY exchange rate. We can see that the traded volume in the WTI crude oil future contracts exhibit a significant explanatory power at the 99% confidence level, followed by the traded volume in the SCPA crude oil future contracts at a 85% confidence level. The U.S. and Chinese-related news sentiment score doesn't exhibit any significant explanatory power to explain the USD/CNY exchange rate.

Table 3 shows the estimation statistics of the aggregated U.S. - and European-related news sentiment score and related financial indicators used as parameters to explain the EUR/USD exchange rate. We can see that the WTI volume also explains the EUR/USD exchange rate at a 99% confidence level, followed by the Brent volume at 97%, and the WTI price at 87%. The U.S. and European-related news sentiment score exhibits a significant explanatory power to explain the EUR/USD exchange rate at a 80% confidence level.

Table 4 reports the estimation statistics of the aggregated European- and Russian-related news sentiment score and related financial indicators used as parameters to explain the EUR/RUB exchange rate. Highly significant explanatory can be found in the EURRUB forward rate at 99.99% confidence level, the Brent price at 99%, followed by IMOEX price at 98% and WTI price at 97%. The European- and Russian related news sentiment score does not exhibit any significant explanatory power to explain the EUR/RUB exchange rate.

Table 5 outlines the estimation statistics of the aggregated Russian- and Chinese-related news sentiment score and related financial indicators used as parameters to explain the RUB/CNY exchange rate. Highly significant explanatory can be found in the IMOEX volume and Brent volume at a 99% confidence level, and the SCPA volume at 98%. The Russian- and Chinese-related news sentiment score doesn't exhibit any significant explanatory power to explain the RUB/CNY exchange rate.

Table 6 delineates the estimation statistics of the aggregated European- and Chinese-related news sentiment score and related financial indicators used as parameters to explain the EUR/CNY exchange rate. The only weak significant explanatory can be found in the SCPA volume at 90% at a 99% confidence level. The European- and Chinese-related news sentiment score does not exhibit any significant explanatory power to explain the EUR/CNY exchange rate.

Table 7 summarizes and ranks the estimation res and provides an overview of the associate Pearson correlation factors between the exchange rates and corresponding news sentiment scores. We can see that the EUR/USD news sentiment score exhibits the only existing weak explanatory power to have an effect on the exchange rate, while no significant relationship can be found in the other country pairs' sentiment score and their corresponding exchange rates.

The correlations are all very weak, but the sign of the correlations can mostly be attributed to the risk-on ad risk-off behavior in financial markets. A positive correlation means that when the sentiment score is positive, that the first denominated currency in the pair is getting stronger due to high demand of the currency, and vice versa. Therefore, the correlation reveals a lot about in which direction money flows when the sentiment between two countries gets better or worse. A negative correlation in EUR/USD means that a positive news related to Europe and the USA will weaken the EUR and strengthen the USD. The reason for this might probably be the import dependency of the U.S. on the EU. We can see the same effect with USD/CNY. A negative correlation in USD/RUB might indicate that negative news related to the U.S. and Russia will strengthen the USD due to the flight to safety. The negative correlation in EUR/RUB and EUR/CNY may be probably mostly attributed to the same reason. The positive correlation in RUB/CNY favors the Russian Rubel in case of positive news coverage involving Russia and China, probably because Russia is exporting a vast amount of natural resources to China and thus, strengthen its currency.

In general, certain financial indicators such as the traded volume in oil future contracts seem to impact the exchange rate more than other indicators. Since most of the corresponding news sentiments do not exhibit a significant explanatory power, it seems that news sentiment does not capture the events and developments in the financial markets sufficiently. The reason for this might be under-reporting or misinterpretation of geo-political and financial news. One conclusion that can be drawn from the results is that better news coverage leads to more awareness among market participants and therefore a higher tendency to consider new in currency trading. The higher coverage ratio of news is an indication for the provision of more liquid, and thus, more efficient markets.

Therefore, the provided ranking here can also be seen as a ranking on quantity of news coverage, respectively market participants' tendency to incorporate news coverage into the valuation of or speculation on the corresponding currency pairs, and thus, provides an insight in the efficiency of the corresponding currency, resp. financial markets.

Factors that need to be taken into consideration of this conclusion are of political nature. Since political considerations are play an important role in news coverage, the results might be heavily skewed, but still reflect the news sentiment as it is published. Also, language barriers and system-adversarial conditions might prohibit a better news coverage.

Moreover, scattered time-frames and time-availability of news data restrict the analysis to certain dates which might not be a representative population. Nevertheless, the results provided in this paper can serve as a sample which provides interesting insights into the relationship and contribution of news sentiment to exchange rate determination and efficient markets.

Conclusion

This article investigates the relative contribution of news sentiment to the foreign exchange rate determination. While political and financial factors are undoubtedly determining the exchange rates between counties, the question arises if the mapping and measurement of these processes through news media explains fully or at least partially FX developments as well. While it is possible to find unique measures for each category, they both can be subsumed in the calculation of a sentiment score of the news publishing the political and or economic developments. The following 6 currency pairs are being investigated: EUR/USD, EUR/RUB, RUB/CNY, EUR/CNY, USD/CNY, and USD/RUB. Correspondingly, the news sentiments of the associated country pairs are being calculated for each currency pair to find out the contribution of each news sentiment on the exchange rate development. Further indicators such as the price and aggregated volume of the WTI, Brent and SCPA crude oil future contracts, the IMOEX Russian stock market index, and the corresponding interest rate differential, measured through the 1-year currency forward rate premium, are included as well.

It is found that only the European - and U.S. - news sentiment score exhibits a weak impact on the EUR/USD exchange rate, while the other country pair news sentiment scores do not exhibit any relevant impact on their corresponding exchange rates. What can be further seen, is that most currency pairs are very dependent on the traded volume in their corresponding oil future contracts. This result is not surprising, since the demand and supply of oil future contracts requires the purchase or sale of the corresponding currency. Since oil future contracts are now not only denominated in USD, but also CNY, it is interesting to see that the impact of CNY-denominated oil future contracts on CNY-involved currency pairs is still secondary after WTI or Brent contracts.

The correlations between the news sentiments and corresponding currency pairs indicate the flow of money in risk-on and risk-off situations when sentiment turns negative or positive. It can be seen that the sentiment scores capture the existing global trade and political structure between the biggest players.

A ranking of the significance reveals which country pair is covered best by news media. The implications are not far-fetched, as a higher ranking implies a better news coverage, which in turn reflects a higher awareness of market participants to consider news in their currency evaluation and provides thus, a measure for the efficiency of the corresponding currency, resp. financial markets.

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Appendix

Table 8. *Regression Statistics for USD/RUB*

SUMMARY OUTPUT USD/RUB

Regression Statistics	
Multiple R	0.877584896
R Square	0.770155249
Adjusted R Square	0.717114153
Standard Error	6.956134643
Observations	33

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	6	4215.537889	702.59	14.51997229	3.24699E-07
Residual	26	1258.083038	48.3878		
Total	32	5473.620928			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	48.83808868	36.70804089	1.33045	0.194923374	-26.61637002	124.2925474
Sent_USDRUB	0.406049267	12.07412552	0.03363	0.973429286	-24.41267119	25.22476972
WTI_p	-0.054737841	0.249173248	-0.21968	0.827837674	-0.566920786	0.457445105
WTI_v	2.24018E-06	1.12147E-05	0.19975	0.843226553	-2.08119E-05	2.52923E-05
IMOEX_p	0.001946398	0.005116308	0.38043	0.706716461	-0.008570323	0.012463119
IMOEX_v	2.3513E-11	1.63178E-11	1.44094	0.161537131	-1.00287E-11	5.70547E-11
USDRUB_Fwd	615.6902088	92.8416751	6.63161	4.92617E-07	424.8514125	806.5290051

Table 9. *Regression Statistics for USD/CNY*

SUMMARY OUTPUT USD/CNY

Regression Statistics	
Multiple R	0.804418313
R Square	0.647088822
Adjusted R Square	0.550840319
Standard Error	0.101895558
Observations	29

ANOVA

	df	SS	MS	F	Significance F
Regression	6	0.418824102	0.069804017	6.723105317	0.00037813
Residual	22	0.228419503	0.010382705		
Total	28	0.647243606			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	5.637507735	0.585959581	9.62098396	2.42682E-09	4.42230194	6.852713529
Sent_USDCNY	0.005982379	0.049493726	0.120871451	0.904890017	-0.096661328	0.108626085
WTI_p	0.00358024	0.005738264	0.623923958	0.539093824	-0.008320191	0.015480671
WTI_v	-2.21881E-07	6.14173E-08	-3.612681826	0.001543565	-3.49253E-07	-9.45095E-08
SCPA_p	0.000874738	0.001085381	0.805926882	0.428910845	-0.001376205	0.00312568
SCPA_v	5.80945E-07	3.88721E-07	1.494504547	0.149249938	-2.25213E-07	1.3871E-06
USDCNE_Fwd	7.692150032	8.099588124	0.949696443	0.352583563	-9.105367641	24.4896677

Table 10. *Regression Statistics for EUR/USD*

SUMMARY OUTPUT EUR/USD

Regression Statistics	
Multiple R	0.972114246
R Square	0.945006107
Adjusted R Square	0.897868485
Standard Error	0.015773331
Observations	14

ANOVA

	df	SS	MS	F	Significance F
Regression	6	0.029927127	0.004988	20.04781	0.000442304
Residual	7	0.001741586	0.000249		
Total	13	0.031668712			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1.218487901	0.047742275	25.5222	3.62E-08	1.105595359	1.331380443
Sent_EURUSD	-0.016668845	0.01155381	-1.44271	0.192312	-0.043989265	0.010651575
Brent_p	0.005202024	0.004155886	1.251724	0.250875	-0.004625084	0.015029132
Brent_v	-1.02088E-07	3.64807E-08	-2.7984	0.026585	-1.88351E-07	-1.58245E-08
WTI_p	-0.006173401	0.00361898	-1.70584	0.131805	-0.014730928	0.002384127
WTI_v	1.86498E-07	5.20484E-08	3.583168	0.008938	6.34232E-08	3.09573E-07
EURUSD_Fwd	-4.920682502	3.590343723	-1.37053	0.212851	-13.41049634	3.569131336

Table 11. *Regression Statistics for EUR/RUB*

SUMMARY OUTPUT EUR/RUB

Regression Statistics	
Multiple R	0.896143802
R Square	0.803073714
Adjusted R Square	0.753842143
Standard Error	11.00447318
Observations	41

ANOVA

	df	SS	MS	F	Significance F
Regression	8	15803.02444	1975.378	16.31217	2.68129E-09
Residual	32	3875.149759	121.0984		
Total	40	19678.1742			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-116.3777438	54.48772776	-2.13585	0.040441	-227.3656133	-5.38987433
Sent_EURRUB	2.648286685	6.263494703	0.422813	0.67526	-10.11003452	15.40660789
WTI_p	-3.20346334	1.309652883	-2.44604	0.020123	-5.871138966	-0.535787713
WTI_v	-6.48853E-06	1.79079E-05	-0.36233	0.719488	-4.29657E-05	2.99886E-05
Brent_p	4.103262678	1.429118981	2.871183	0.007196	1.192242574	7.014282781
Brent_v	1.93447E-05	1.71637E-05	1.127068	0.268095	-1.56167E-05	5.4306E-05
IMOEX_p	0.021717761	0.008427736	2.576939	0.014783	0.004551024	0.038884498
IMOEX_v	-1.36283E-11	2.47778E-11	-0.55002	0.586124	-6.40991E-11	3.68424E-11
EURRUB_Fwd	198.2203359	39.62709477	5.002142	1.97E-05	117.5025852	278.9380865

Table 12. *Regression Statistics for RUB/CNY*

SUMMARY OUTPUT RUB/CNY

Regression Statistics	
Multiple R	0.925383568
R Square	0.856334747
Adjusted R Square	0.810361866
Standard Error	0.0073883
Observations	34

ANOVA

	df	SS	MS	F	Significance F
Regression	8	0.008134314	0.001016789	18.62695418	9.65987E-09
Residual	25	0.001364675	5.4587E-05		
Total	33	0.009498989			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.086048294	0.081055282	1.061600089	0.298565609	-0.080888183	0.252984772
Sent_RUBCNY	0.001539436	0.003663499	0.420209331	0.677922332	-0.00600568	0.009084553
IMOEX_p	-6.38796E-06	1.15987E-05	-0.550749026	0.586694152	-3.02759E-05	1.75E-05
IMOEX_v	-8.90655E-14	2.8962E-14	-3.075249638	0.005035851	-1.48714E-13	-2.94171E-14
SCPA_p	0.000101406	6.16022E-05	1.646144252	0.112249603	-2.5466E-05	0.000228278
SCPA_v	6.47239E-08	2.69073E-08	2.40544173	0.023877659	9.30732E-09	1.20141E-07
Brent_p	0.000256204	0.000500579	0.511815111	0.613272032	-0.000774757	0.001287165
Brent_v	-2.76817E-08	7.66805E-09	-3.610010372	0.001338554	-4.34744E-08	-1.18891E-08
RUBCNY_Fwd	8.375501204	5.135454153	1.630917336	0.115443364	-2.20116461	18.95216702

Table 13. *Regression Statistics for EUR/CNY*

SUMMARY OUTPUT	EUR/CNY
Regression Statistics	
Multiple R	0.877983875
R Square	0.770855685
Adjusted R Square	0.700349742
Standard Error	0.115643086
Observations	35

ANOVA

	df	SS	MS	F	Significance F
Regression	8	1.169705918	0.14621324	10.93320153	1.31339E-06
Residual	26	0.347706408	0.013373323		
Total	34	1.517412326			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	8.839188854	0.632964764	13.96474078	1.35708E-13	7.538111148	10.14026656
Sent_EURCNY	-0.01558727	0.044715519	-0.348587471	0.730206024	-0.107501336	0.076326796
SCPA_p	-0.00188232	0.001495291	-1.25883146	0.219277064	-0.004955934	0.001191295
SCPA_v	-5.31726E-07	3.10533E-07	-1.712300475	0.098745234	-1.17004E-06	1.06584E-07
Brent_p	-0.018920255	0.012793593	-1.478885231	0.151185396	-0.045217862	0.007377351
Brent_v	-1.31873E-07	1.78708E-07	-0.737925166	0.467168474	-4.99213E-07	2.35467E-07
WTI_p	0.016395213	0.011334523	1.446484674	0.159990201	-0.006903232	0.039693658
WTI_v	1.11999E-07	1.62691E-07	0.688414176	0.497289019	-2.22417E-07	4.46415E-07
EURCNY_Fwd	-2.631062885	3.239616993	-0.812152452	0.424078035	-9.290190984	4.028065215