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Tomáš Plíhal

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TOMÁŠ PLÍHAL

Department of Finance

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Annotation

This collection of essays contains six published academic papers related to volatility modeling and forecasting. It includes the introductory chapter about the importance of volatility and different volatility models, followed by a summary of the papers. Each section states the bibliographic record and my personal contribution to each paper, along with the article's contribution to academic literature, a summary of the relevant literature, methodology, and main results, ending with potential research limits. Lastly, the conclusion summarizes the thesis and indicates the expected future direction of my research.

Acknowledgements

This habilitation thesis would not have been possible without the enormous support of many people. The main credit for this goes to Štefan Lyócsa, my former Ph.D. supervisor, who taught me a lot and became a valued co-author. Next, I really appreciate the support of my colleagues, especially Oleg Deev, Dagmar Vágnerová Linnertová, and Filip Hampl. They have created a perfect working environment, are always willing to help, and have become great companions. Last but not least, my thanks go to my wife, who provided me with enough peace and comfort at home, allowing me to deliver high-quality work.

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Introduction

This collection of essays contains six papers from the field of volatility modeling and forecasting. The understanding of volatility is crucial for understanding price behavior. It can help with more efficient asset allocation, market risk management, or financial derivatives valuation. Volatility might also be traded using options or artificial indices linked to market volatility (Poon et al., 2003). Therefore, modeling and forecasting volatility has received considerable attention in the financial literature (e.g. Engle, 1982; Bollerslev, 1986; Andersen; Bollerslev, 1998; Corsi, 2009).

The volatility of a financial asset represents the fluctuation of its price. In other words, it measures how quickly and how much the price changes. However, it does not represents the direction of such price movements. It is also closely connected with the trading activity of market participants, where higher volatility is usually connected with increased trade volume indicating changes in the expectation of investors about the future prices of a given asset.

The central role plays various expected and unexpected events that have the power to drive the market prices and their volatility. Volatility plays a central role in finance and is often perceived as a measure of risk because it represents an uncertainty of the future development of asset prices. Moreover, it is often used as a proxy of asset-market-base uncertainty (e.g. Andersen; Bollerslev, 1998; Andersen; Bollerslev; Diebold; Ebens, 2001; Andersen; Bollerslev; Diebold; Labys, 2003; Andersen; Bollerslev; Diebold, 2007; Corsi, 2009; Corsi; Renò, 2012; Bollerslev; Hood, et al., 2018; Cascaldi-Garcia et al., 2021)

This essay collection is divided into four main chapters. Chapter 1 provides a brief review of volatility models and their historical development. This chapter aims to motivate the model selection in the following chapters and introduce the primary literature related to volatility modeling and forecasting.

Chapter 2 focuses on two papers that examine the effect of implied volatility and the data sampling frequency for realized volatility forecasting. Both papers focused on foreign exchange markets and enriched the academic literature in this field. We provide new empirical evidence that implied volatility from short-term options (one day and one week) is highly relevant for forecasting realized volatility of the next day. In the paper about data sampling frequency, we confirm that high-frequency data are superior to low-frequency counterparts. However, this advantage is statistically significant only for short forecast horizons (less than five days). For longer forecast horizons, low-frequency data become competitive.

Chapter 3 contains two papers that analyzed the effect of news announcements and other events on the stock market volatility and the volatility of bitcoin. The third essay sheds new light on the issue of the Central bank announcements and realized volatility of stock markets in G7 countries. It focuses on the impact of policy rates and quantitative easing announcements of domestic and foreign central banks on realized volatility before, during, and after the event. The results show that volatility increases on the day of an interest rate announcement by the domestic central bank. Additionally, evidence indicates a volatility decline five days after an interest rate announcement across all countries in the analyzed sample. The results also show that quantitative easing announcements have no impact on stock market volatility.

The fourth essay shifts the focus to the volatility of bitcoin, which incredible price appreciation, especially during the year 2017, attracted much attention not only from speculative investors but also from the academic literature. The essay focuses on the effect of news and sentiment about bitcoin regulation, the hacking of bitcoin exchanges, and scheduled macroeconomic news announcements on the realized volatility of bitcoin and its jump component. The results show that realized variance and its jump component exhibit similar dynamics and react similarly to various types of news. The volatility of bitcoin reacts most strongly to news on bitcoin regulation, positive investor sentiment regarding bitcoin regulation extracted using Google searches, and most notably, hacking attacks on cryptocurrency exchanges. Quantile regression reveals that hacking attacks have a powerful impact on the upper conditional distribution of bitcoin volatility. The analysis also provides evidence that the volatility of bitcoin is not influenced by most scheduled US macroeconomic news announcements, such as government budget deficits, inflation, or even monetary policy announcements. On the other hand, bitcoin responds with increased volatility to announcements of forward-looking indicators, such as the consumer confidence index.

Chapter 4 shows the last two essays focusing on the two most recent crises related to the COVID-19 pandemic and the Russo-Ukrainian war in early 2022. Both events created unprecedented volatility in financial assets and provided valuable information to help us understand the volatility behavior during such extreme periods. The essay about the COVID-19 pandemic analyzes the stock market realized volatility in 23 countries. It focuses on the effect announcements of policy interventions and responses intended to buffer the pandemic's short-term economic impact and offset financial turmoil. Under the augmented heterogeneous autoregressive model framework, the results indicate that the international calming effect of COVID-19 economic policy actions originates from the US macroprudential policy announcements.

The last essay analyzed the beginning of the Russo-Ukrainian crisis in early 2022 that led to the rapid depreciation of the Russian ruble. It models intraday price fluctuations of the USD/RUB and the EUR/RUB exchange rates from the 1^{st} of December 2021 to the 7^{th} of March 2022. It utilizes a novel approach to this issue by using intraday (high-frequency) data of google searches and implied volatility instead of commonly used daily data. Google searches and implied volatility represent the investor's attention and expectations proxies. The results indicate that both approaches help predict intraday price fluctuations of the two exchange rates, although implied volatility encompasses intraday attention.

At the end of this habilitation thesis is a conclusion summarizing the previous chapters. The full texts of all essays presented in this thesis are provided in the Appendix A.

1 A Brief Review of Volatility Models

A large number of realized volatility models were developed during the last several decades. One of the stylized facts of financial time series is so-called time-varying volatility clustering. In simple terms, it means that there are observable periods of high volatility followed by periods of low volatility and vice versa. This stylized fact is exploited by the popular autoregressive conditional heteroskedasticity model (ARCH) by Engle (1982). The simplest version of this model is defined as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 \tag{1.1}$$

where σ_t^2 is the conditional variance at time t, $\alpha_0 \ldots \alpha_i$ are estimated coefficients, and ϵ_{t-i}^2 is a random error. A few years after the ARCH model, probably the most famous extension of this model was developed, called the generalized ARCH model (GARCH) by Bollerslev (1986). The structure is similar to the basic ARCH model but with added lagged values of volatility σ_{t-j}^2.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{1.2}$$

The ARCH and GARCH models were initially estimated on low frequency (usually daily) data. Researchers continued to extend and modify these models to capture specific stylized facts for various time series. Some of these variations include, for example, nonlinear GARCH (NGARCH; Lanne et al., 2005), integrated GARCH (IGARCH; Engle; Bollerslev, 1986), exponential GARCH (EGARCH; Nelson, 1991), quadratic GARCH (QGARCH; Sentana, 1995), GJR-GARCH Glosten et al. (1993) and many others (for an early review, see Poon et al., 2003).

Financial time series often exhibit much more stylized facts than only volatility clustering. Among the essential characteristics usually belong long-memory, fat tails, or self-similarity. These properties could be very challenging for econometric models, and a standard GARCH model is not able to replicate all of these properties due to its short-memory nature. There exist some models that are able to capture the long-memory by using the fractional difference operators, e.g., FIGARCH (Baillie et al., 1996) or ARFIMA (Granger et al., 1980). However, these models are hard to fit and also contain other complications, such as a lack of clear economic interpretation.

With the increased availability of intraday high-frequency data, the new family of models emerged based on the Heterogeneous Autoregressive models of Realized

Volatility (HAR-RV) developed by Corsi (2009) which uses realized volatility estimators of Andersen; Bollerslev (1998) and Andersen; Bollerslev; Diebold; Ebens (2001). The basic form of the model is defined as follows:

$$RV_t = \beta_1 + \beta_2 RV_{t-1}^{D} + \beta_3 RV_{t-1}^{W} + \beta_4 RV_{t-1}^{M} + \epsilon_t \tag{1.3}$$

RV_t is a realized volatility in day t and RV_{t-1}^{D}, RV_{t-1}^{W}, RV_{t-1}^{M} represent are average volatilities over the past day, week, and month.

This model does not have typical characteristics of a long-memory model but is still able to reproduce most of the volatility stylized facts, including long-memory (e.g., Andersen; Bollerslev; Diebold, 2007; Vortelinos, 2017). Moreover, the model is easy to estimate and economically intuitive. Its ordinary least squares properties allow us to add other regressors effortlessly and calculate their significance levels. The original HAR model was also modified by the decomposition of realized volatility to continuous and jump components (e.g., Andersen; Dobrev, et al., 2012), the use of semivariances and signed jumps (Patton; Sheppard, 2015), the inclusion of measurement error (Bollerslev; Patton, et al., 2016), the incorporation of nontrading volatility components (Lyócsa; Molnár, 2017; Lyócsa; Todorova, 2020) or the use of hidden Markov chains (Luo et al., 2022), to name a few. It is also possible to use a multivariate version of the HAR model (Chiriac et al., 2011; Bauer et al., 2011; Čech et al., 2017).

There is robust empirical evidence suggesting that models of volatility based on high-frequency estimators provide superior forecasts compared to models based on low-frequency data (e.g., Koopman et al., 2005; Andersen; Bollerslev; Diebold, 2007; Corsi; Pirino, et al., 2010; Busch et al., 2011; Horpestad et al., 2019). However, there is a possible issue with the microstructure noise in the high-frequency data. As a result, high-frequency estimators of volatility worked well only for assets with significant trade volume and high-quality data. Otherwise, the results could be biased and inefficient (Andersen; Bollerslev; Diebold; Ebens, 2001). Many researchers tried to solve this issue by creating alternative estimators of volatility (e.g., Ait-Sahalia et al., 2005; Bandi et al., 2008; Barndorff-Nielsen; Hansen, et al., 2008; Andersen; Bollerslev; Meddahi, 2011; Liu et al., 2015).

There also exist approaches that try to merge GARCH-type models with high-frequency volatility estimators. The primary model in this category is represented by the realized-GARCH model from Hansen; Z. Huang, et al. (2012), followed by several alternative models (e.g., Xie et al., 2020; Wu et al., 2021).

The selected six essays in the following chapter predominantly utilize the various modifications of the HAR class models of volatility. The choice of this type of model was based on their relatively very good in-sample as well as out-of-sample performance, computational efficiency, and the possibility to add additional variables and measure their statistical significance easily. The model also allows to include different volatility estimators, various decomposition of volatility, or forecast only some specific part of volatility, such as volatility jumps.

2 Realized Volatility Forecasting

The first two papers in this essay collection focus on forecasting realized volatility. The first paper challenges the idea that high-frequency data are superior to daily data for forecasting purposes. We contribute to the literature by providing the evidence that this statement is valid only for a short forecasting horizon, and daily data are also able to provide comparable forecasts and offer other additional advantages. The second paper focuses on the information content of implied volatility for forecasting realized volatility. Our contribution demonstrates that the quoted implied volatility on the foreign exchange market is highly relevant for realized volatility forecasting due to its forward-looking nature.

2.1 FX market volatility modelling: Can we use low-frequency data?

Table 1: Paper Information and Author Contribution

Reference
Lyócsa, Š., Plíhal, T., & Výrost, T. (2021).
FX market volatility modelling: Can we use low-frequency data?
Finance research letters, 40, 101776.

Journal Rankings 2021	**Citations**
WoS AIS: 1.245 (Q2)	WoS: 3
WoS IF: 9.848 (Q1)	Scopus: 3
	Scholar: 4

My Contribution (33%)
Conceptualization, Methodology, Data curation, Investigation
Writing - original draft, Writing - review & editing

Note: Author contribution stated as percentage share and specified using CRediT author statement by Elsevier. Citations were collected in August 2022 and included self-citations.

As mentioned in the previous chapter about volatility models, high-frequency data are theoretically preferred (Andersen; Bollerslev; Diebold; Ebens, 2001) and often provide superior forecasts for one-day time horizons (e.g., Koopman et al., 2005; Andersen; Bollerslev; Diebold, 2007; Corsi; Pirino, et al., 2010; Busch et al., 2011; Horpestad et al., 2019). Surprisingly, the academic evidence for longer forecast horizons is mostly missing. We assume that for longer prediction (e.g., one month ahead), the information content of intraday price fluctuations decreases, and daily data could offer comparable forecasts.

Daily data would provide many benefits, e.g., lower microstructure noise, lower space and computational requirements, high availability, etc.

In this study, we fill the gap in the literature and compare the forecasting accuracy of several volatility models as a function of the forecast horizon on the six major currency pairs. Our results confirm the dominance of high-frequency data estimators for forecasting one-day-ahead volatility. However, for longer forecast horizons (5-days or more), low-frequency models can provide statistically comparable results. These findings provide important insights for practitioners and policymakers to help them to choose low- or high-frequency volatility models for a particular setting.

2.1.1 Data and Methodology

The study analyzes major foreign exchange market pairs: AUD/USD, EUR/USD, GBP/USD, USD/CAD, USD/CHF, and USD/JPY. This choice was motivated by the high liquidity of selected assets and the high quality and availability of high-frequency data necessary for meaningful analysis. The data were collected from OANDA using a 5-minute calendar sampling over a 24-hour trading window. The whole sample covers the period from May 2005 to the end of September 2019.

A high-frequency volatility estimator is represented by the sum of intraday 5-minute squared returns, which is the most common choice in academic literature (e.g., Andersen; Bollerslev, 1998; Andersen; Bollerslev; Diebold; Ebens, 2001; Liu et al., 2015). Low-frequency volatility estimators are calculated from daily open, high, low, and close prices. We use three versions of estimators according to Parkinson (1980), Garman et al. (1980), and Rogers et al. (1991). Moreover, motivated by Patton; Sheppard (2009) we take the average of these three estimators because the forecast combination could increase the efficiency of the estimation process.

We choose three volatility models suitable for low- and high-frequency data and, simultaneously, capable of replicating long memory and volatility clustering effects. The models are the heterogeneous autoregressive model (HAR) of Corsi (2009), the autoregressive fractionally integrated model (ARFIMA), and the realized generalized autoregressive conditional heteroscedasticity (realized-GARCH) of Hansen; Z. Huang, et al. (2012).

We use the standard specification of the HAR model with a few modifications. First, we added a fourth volatility component that represents three-month realized volatility. It is motivated by the fact that our forecasting horizon ranges from one day to three months. Moreover, we tried the specification that utilizes positive and negative semivariances (Patton; Sheppard, 2015) that captures the asymmetric volatility response. The last specification is motivated by Corsi; Reno (2009) and Horpestad et al. (2019), which utilize absolute returns that are usually correlated with variance. All versions of the HAR model are estimated using weighted least squares, where weights are reciprocal values of the dependent variable (Clements et al., 2021).

Our ARFIMA-GARCH model uses the mean equation specified as:

$$RV_t = \alpha + u_t \tag{2.1}$$

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1 - L)^d u_t = \left(1 + \sum_{j=1}^{q} \theta_j L^j\right) \varepsilon_t \tag{2.2}$$

$$\varepsilon_t = v_t \eta_t, \text{ where } \eta_t \sim iid(0, 1) \tag{2.3}$$

where d is the differencing parameter (e.g., Granger et al., 1980), v_t is the time-varying volatility and η_t is an *iid* variable following a flexible distribution (Johnson, 1949b; Johnson, 1949a). The variance equation is the exponential GARCH model of Nelson (1991):

$$\ln v_t^2 = \omega + \alpha z_{t-1} + \gamma\left(|z_{t-1}| - E|z_{t-1}|\right) + \beta \ln v_{t-1}^2 \tag{2.4}$$

The sign and the size effects are captured by α and γ, and z_t is the standardized innovation.

Finally, the realized GARCH model of Hansen; Z. Huang, et al., 2012 uses the mean equation of daily returns:

$$R_t = \kappa + u_t \tag{2.5}$$

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1 - L)^d u_t = \left(1 + \sum_{j=1}^{q} \theta_j L^j\right) \varepsilon_t \tag{2.6}$$

$$\varepsilon_t = v_t \eta_t, \text{ where } \eta_t \sim iid(0, 1) \tag{2.7}$$

The variance and the measurement equations are:

$$\ln v_t^2 = \omega + \alpha \ln RV_{t-1} + \beta \ln v_{t-1}^2 \tag{2.8}$$

$$\ln RV_t = \xi + \delta \ln v_t^2 + \lambda_1 z_t + \lambda_2 (z_t^2 - 1) + w_t\,,\, w_t \sim N(0, \theta) \tag{2.9}$$

Each of the mentioned models is estimated with low-frequency volatility estimator and then with an estimator based on high-frequency data. The out-of-sample forecasting procedure uses a rolling window of 1000 days. To mitigate model uncertainty, we apply a combination of forecasts based on weighted averages with weights given by discounted forecast error. We combine low-frequency models, high-frequency models, and all models. Volatility forecasts are then evaluated using two statistical loss functions (mean square error and quasi-likelihood) and model confidence set by Hansen; Lunde, et al. (2011).

2.1.2 Results

To compare the predictive abilities of low- and high-frequency models, we forecast volatility for one day and up to three months ahead, calculate the loss functions, and estimate if there is some statistically significant difference between the forecasts.

For most cases, high-frequency models could provide slightly lower values of the loss functions, which indicates better performance. Still, this difference became quickly statistically insignificant with a longer forecast horizon (more than five days). Moreover, the combination of the forecasts proves to be beneficial for all forecast horizons. These results can be generalized for all our exchange rates and loss functions.

When analyzing the results a bit deeper, we found that the low-frequency model forecasts tend to be more biased, especially for shorter forecast horizons, compared to high-frequency models. It suggests that resolving the bias could further improve forecasting accuracy. Finally, we study how the difference between the accuracy of high- and low-volatility forecasting models changes over time and in high-/low-volatility periods. The results suggest that high-frequency models tend to be superior during periods of increased volatility.

We conclude that if high-frequency data are not available, then low-frequency data can be used to estimate and predict long-term market volatility. These results have implications for researchers and investors alike, as they demonstrate that low-frequency volatility models can provide competitive performance to that of high-frequency models under some circumstances. Our study notes that high-frequency data might not always be worth the much higher acquisition, data management, and processing costs, especially if the forecast horizon of interest is sufficiently long.

This paper contains several limitations. It is focused solely on the major currency pairs from the foreign exchange market. Even though the results provide some intuition on how the volatility forecasts behave, it is not recommended to generalize the results for all assets without further analysis. Moreover, we focused on forecasting performance, not the performance in real applications. The results could become more or less statistically significant for specific applications, like risk management, portfolio management, or valuation of assets.

2.2 Modeling realized volatility of the EUR/USD exchange rate: Does implied volatility really matter?

Table 2: Paper Information and Author Contribution

Reference
Plíhal, T. & Lyócsa, Š.(2021).
Modeling realized volatility of the EUR/USD exchange rate:
Does implied volatility really matter?
International Review of Economics & Finance, 71, 811-829.

Journal Rankings 2021	Citations
WoS AIS: 0.572 (Q3)	WoS: 3
WoS IF: 3.399 (Q2)	Scopus: 4
	Scholar: 8

My Contribution (50%) - Corresponding author
Methodology, Formal analysis, Investigation
Writing - original draft, Writing - review & editing

Note: Author contribution stated as percentage share and specified using CRediT author statement by Elsevier. Citations were collected in August 2022 and included self-citations.

We can distinguish two main types of volatility. The first type is realized or historical volatility. It is calculated from historical data and represents the past behavior of the financial asset. The most simple estimator of this type of volatility is a standard deviation of prices for a selected time period. However, a large body of various estimators of historical volatility exists, and each of them can capture slightly different information from the historical prices. The second type of volatility is implied volatility estimated from the prices of financial derivatives. As a result, it represents the expected volatility of the underlying asset of the specified derivative. In other words, it captures the market view on the future development of volatility.

Because of the forward-looking nature of implied volatility, there is a question of whether it can improve the forecasting performance of realized volatility models. This issue was studied in the academic literature, but the results are mixed. Canina et al. (1993), Becker; Clements; White (2006), Becker; Clements; White (2007), and Becker; Clements (2008) found very little incremental information of implied volatility. On the other hand, Day et al. (1992), Christensen et al. (1998), Blair et al. (2001), Busch et al. (2011), Han et al. (2013), Kambouroudis et al. (2016), Y.-H. Wang et al. (2016), and Kourtis et al. (2016) claimed that implied volatility is useful and contributes to realized volatility models. Moreover, Christensen et al. (1998) and Blair et al. (2001) argue that implied volatility can capture all necessary information for realized volatility forecasting, and we do not need to use realized volatility at all.

All the mentioned studies focused on the stock market, and literature about other assets is scarce. The foreign exchange market was examined in Jorion (1995), Xinzhong et al. (1995), Pong et al. (2004), Covrig et al. (2003), and Busch et al. (2011) but also with the mixed results. Additionally, most studies relied on implied volatility derived from options with 30-day maturity even though there exist options with even shorter maturities that could provide more precise information about the near future.

Our contribution to the academic literature is threefold. First, current literature usually works only with implied volatility representing one-month maturity. Therefore, we focus our analysis on foreign exchange implied volatility with different maturities: one day, one week, and one month. Second, the existing literature seems to suggest that the role of implied and historical volatility differs concerning the forecast horizon. However, the recent evidence is based mainly on at least one-month-ahead forecasts. We fill this gap in the literature and provide evidence for three different forecast horizons. Third, we employ several volatility model specifications and combination forecasts to address the possibility that the findings from previous studies might have been subject to volatility model choice uncertainty. We compare individual forecasting models that: a) separate volatility into positive and negative semi-volatilities, b) separate the continuous volatility component and the jump component, c) weight volatility based on the estimated variance of the measurement error. We also try to improve the forecast through model combination.

2.2.1 Data and Methodology

Our study covers 12 years of data from 2006 to the end of 2017 and focuses on one of the most liquid markets in the world, the EUR/USD exchange rate. Realized volatility is calculated from high-frequency data provided by DucasCopy. Implied volatility is collected from Bloomberg and represents quoted implied volatility for EUR/USD options traded on the over-the-counter market. Both time series are synchronized to the same time zone, weekends are removed, and a 24-hour trading day is used.

Our methodology is based on the HAR model of Corsi (2009) and its modifications. The simple HAR model is specified as follows:

$$RV_{t+1}^{H} = \beta_1 + \beta_2 RV_t^{D} + \beta_3 RV_t^{W} + \beta_4 RV_t^{M} + \epsilon_{t+1} \tag{2.10}$$

where RV_{t+1}^{H} is the average daily realized volatility over the next H days, i.e., the forecast horizon. In this study, we consider H = 1, 5, and 22, i.e., forecasts of intra-day volatility over the next one, five, and twenty-two trading days, respectively. RV_t^D, RV_t^W, and RV_t^M are the averages of realized volatility over the previous one, five, and twenty-two trading days, respectively. These volatility components should mimic daily (D), weekly (W), and monthly (M) volatility trends.

Then, we create the same model but replace the right-hand side variables with implied volatilities with corresponding maturities:

$$RV_{t+1}^{H} = \beta_1 + \beta_2 IV_t^D + \beta_3 IV_t^W + \beta_4 IV_t^M + \epsilon_{t+1} \tag{2.11}$$

Both models are then combined into one model with both realized and implied volatility components:

$$\begin{aligned} RV_{t+1}^{H} = \beta_1 + \beta_2 RV_t^D + \beta_3 RV_t^W + \beta_4 RV_t^M + \\ \beta_5 IV_t^D + \beta_6 IV_t^W + \beta_7 IV_t^M + \epsilon_{t+1} \end{aligned} \tag{2.12}$$

Following a similar fashion, we tried three modifications of the basic HAR model. First, we use the decomposition of realized volatility to its continuous component (CC) and jump component (JC), according to Andersen; Dobrev, et al. (2012). The second modification follows the work of Bollerslev; Patton, et al. (2016) and controls for measurement error. The third version of the model decomposes realized volatility into positive and negative semivariances (Patton; Sheppard, 2015). All models are estimated in the realized volatility specifications and then augmented by implied volatility components, as in the simple HAR model.

Lastly, we try the forecast combination of all model forecasts that do not contain implied volatility compared to the combination of all models that include implied volatility information. We choose the simple average of individual forecasts as a method for combining model predictions because it proves to be a safe and effective approach (e.g., Genre et al., 2013; Santos et al., 2014; Lyócsa; Molnár, 2016; Lyócsa; Molnár; Todorova, 2017).

Forecasting performance is then evaluated using two loss functions, MSE and QLIKE, that provide a consistent ranking of forecasts (Patton, 2011). Moreover, we apply the model confidence set by Hansen; Lunde, et al. (2011).

2.2.2 Results

Our results provide new empirical evidence suggesting that implied volatilities from options with a one-day and one-week maturity might be more relevant when explaining the volatility of the next one day and one week on the EUR/USD exchange rate. The inclusion of implied volatility usually decreased the size of the realized volatility coefficients, and the fit of the models improved by up to 29%, 27%, and 9% for the one-day, one-week, and one-month-ahead forecasts, respectively.

The results also indicate that realized volatility is still beneficial because the models that include both types of volatility usually provide greater fit and forecasting performance. However, the improvements achieved by including realized volatility in the model are smaller than in the case of implied volatility. Moreover, the forecast horizon is also essential, and implied volatility's importance increases with the lower forecast horizon.

Finally, our out-of-sample analysis confirms the incremental information of implied volatility. The model confidence set always chooses only the models that contain implied volatility in the superior set of models. These results are supported by estimated improvements in forecasting accuracy as measured by loss functions MSE and QLIKE. These results are supported by all model specifications, forecast horizons, and even model combinations.

The main limit of this paper is only one selected asset, EUR/USD. Further analysis is needed to confirm the results for different currency pairs or other assets. The potential assets are limited by the availability of good quality high-frequency data and liquid over-the-counter options market with quoted implied volatility data.

3 News Announcements and Realized Volatility

This chapter presents two essays explaining volatility and the effects of various events. The first paper focuses on the stock markets of the developed countries and examines the announcements of the central banks. The paper's main contribution is to show volatility behavior several days before and after the announcement and provide robust evidence in a multicountry study. The second paper analyzes the cryptocurrency Bitcoin, which was on a large boom. It examines the connection of bitcoin to the real economy by measuring the reaction of volatility to various macroeconomic news announcements. The study also included other events related to policy regulation of cryptocurrencies and hacking attacks that lead to significant financial losses of invested money and increased uncertainty about this asset.

3.1 Central bank announcements and realized volatility of stock markets in G7 countries

Table 3: Paper Information and Author Contribution

Reference
Lyócsa, Š., Molnár, P., & Plíhal, T. (2019).
Central bank announcements and realized volatility
of stock markets in G7 countries.
Journal of International Financial Markets, Institutions and Money, 58, 117-135.

Journal Rankings 2019	**Citations**
WoS AIS: 0.574 (Q2)	WoS: 8
WoS IF: 2.553 (Q1)	Scopus: 7
	Scholar: 20

My Contribution (33%)
Conceptualization, Methodology, Data curation, Investigation,
Writing - original draft, Writing - review & editing

Note: Author contribution stated as percentage share and specified using CRediT author statement by Elsevier. Citations were collected in August 2022 and included self-citations.

Macroeconomic news announcements are one of the drivers of price changes in financial assets. It allows market participants to update their expectations about future asset prices and adjust their positions accordingly. Due to the importance of this topic, a large body of literature assesses the impact of macroeconomic news announcements on financial markets. The literature focused on various asset classes, for example:

- *Stock markets:* Flannery et al. (2002), Ehrmann et al. (2004), Bernanke et al. (2005), Bekaert; Engstrom (2010), and Hussain (2011).
- *Foreign exchange markets:* Almeida et al. (1998), Andersen; Bollerslev; Diebold; Vega (2003), Ehrmann et al. (2005), Evans et al. (2010), Ben Omrane et al. (2015), Petralias et al. (2015), El Ouadghiri; Uctum (2016), and Neely et al. (2010).
- *Government bond markets:* Fleming et al. (1997), Fleming et al. (1999), Christie-David et al. (2002), Balduzzi et al. (2001), Gürkaynak et al. (2005), Beechey et al. (2009), and El Ouadghiri; Mignon, et al. (2016).
- *Several asset classes:* Boyd et al. (2005), Faust et al. (2007), and Bartolini et al. (2008).

One of the most important macroeconomic announcements is related to the central bank, and market participants pay particular attention to these types of news (e.g., Thorbecke, 1997; Thornton, 1998). Studies that focused on asset price volatility reported often increased volatility during these announcements (e.g., Harvey et al., 1991; Ederington et al., 1993; Dominguez, 1998; Nikkinen; Sahlström, 2001; Bauwens et al., 2005; Dominguez, 2006; Nikkinen; Omran, et al., 2006; Beine et al., 2009, and many others).

We study the impact of central bank announcements on the volatility of equity markets. In particular, we want to determine whether monetary policy decisions have a stabilizing or a destabilizing impact on equity markets. The previous literature does not offer a satisfactory answer to our question. Although the previous literature documents an increase in volatility around news announcements, this cannot be interpreted as finding that announcements have a destabilizing impact on financial markets. The information content of news is usually high; therefore, it is only natural that volatility is high around earnings announcements. For example, Chae (2005) argues that if the information content of news is high, it will necessarily increase volatility in the market because market participants adjust their views based on the news provided. Thus, the consensus of market participants increases on the day of the news announcement.

A possible way to analyze some announcements' stabilizing or destabilizing impact is to evaluate volatility several days before and after the announcement. It was addressed before in the literature but not to a satisfactory extent. The literature used daily data and the GARCH framework (e.g., Bomfim, 2003; S.-J. Kim et al., 2004; Bauwens et al., 2005) or implied volatility (e.g., Ederington et al., 1993; Nikkinen; Sahlström, 2004; Äijö, 2008; Aktas, 2011; Füss et al., 2011; Jiang et al., 2012; Marshall et al., 2012; Krieger et al., 2015). However, volatility models estimated from daily data cannot reliably estimate whether and how much volatility increased on a particular day. On the other hand, implied volatility represents expectations about future volatility and therefore decreases artificially after the announcement day drops from the expected future window (usually 30 days).

Our contribution to the literature is three-fold. First, most papers studying the impact of monetary policy announcements on financial markets study foreign exchange markets, not stock markets. Second, we use a multi-country sample, five central banks and their impact on the volatility of eight stock market indices while controlling for the news announcements of other central banks and news related to quantitative easing policies. Third, and most importantly, the literature in this field is based on implied volatility, and implied volatility mechanically declines after the scheduled announcements.

3.1.1 Data

Our sample covers the seven major advanced economies (G7) according to the International Monetary Fund (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States). The analyzed time period begins in January 2006 and ends in November 2016. The dataset consists of three main parts: stock market indices, news announcements from central banks, exchange rate and interest rate.

Stock market indices data with precalculated volatility measures are collected from the Oxford-Man Institute of Quantitative Finance Realized Library[1]. The analyzed indices are S&P 500 (United States), FTSE 100 (United Kingdom), TSX (Canada), NIKKEI 225 (Japan), STOXX 50 (Europe), DAX (Germany), CAC (France), and MIB (Italy).

The news announcements dataset focuses on the most important macroeconomic news announcements related to the central banks: target interest rates and quantitative easing. The data were downloaded from Bloomberg and contain interest rate decisions from the Bank of Canada, European central bank, Bank of Japan, Bank of England, and Federal Reserve Board. The data about quantitative easing were downloaded manually from the official sites of the central banks, and we selected the days when the introduction of quantitative easing or any change in this policy was announced. Quantitative easing is an unconventional monetary policy used by central banks to stimulate their economies when conventional monetary policy is no longer effective and usually consists of purchasing long-term financial assets from banks and other financial institutions. During our sample period, all the selected countries except Canada have experienced quantitative easing.

1. http://realized.oxford-man.ox.ac.uk/data/download

The last part of the dataset consists of information about short-term interest rates (3 months) and effective exchange rates. The data are obtained from Bloomberg at a daily frequency for each country.

3.1.2 Methodology

In this study, we focus on stock market volatility. However, many different volatility estimators exist, each of which could contain slightly different information about volatility. Therefore, we employ a methodology suggested by Patton; Sheppard (2009) who advocates using a combination of various realized measures. As a result, we calculate a simple arithmetic average of the eight standard realized volatility measures. In all our calculations, we use the logarithm of the resulting mean realized variance, i.e., realized volatility, because the distribution of the realized variances tends to be skewed to the right and is subject to outliers.

We measure the impact of news announcements for each index separately using a Heterogeneous AutoRegressive model with eXogenous variables and Generalized AutoRegressive Conditional Heteroskedastic errors (DHARX-GARCH). The model specification is as follows:

$$\Delta RV_t = \mu_0 + \mu_1 RV_{t-1} + \mu_2 RV_{t-1,t-5} + + \mu_3 RV_{t-1,t-22} + \sum_{s=1}^{S(i)} \kappa_s EV_s + \sum_{c=1}^{C(i)} \delta_c CV_c + z_t \tag{3.1}$$

$$z_t = (1 + \Theta_1 L^1)\epsilon_t \tag{3.2}$$

$$\epsilon_t = \sigma_t \eta_t, \ \eta_t \approx iid(0,1) \tag{3.3}$$

We model differences of the RV_t and level of RV_t as a robustness check. The core explanatory variables are inspired by the heterogeneous autoregressive model (HAR) by Corsi (2009) that represents the lag of the daily, weekly, and monthly volatility. Then we included event variables (EV_s) and control variables (CV_c).

Although the lagged realized volatilities and other exogenous variables capture most of the market volatility dynamics, the error term z_t may remain subject to autocorrelation and conditional heteroscedasticity. We, therefore, model the term z_t as a moving average process (L is the lag operator), whereas we allow the evolution of σ_t^2 to follow a suitable GARCH model. Two GARCH models are considered: the standard model of Bollerslev (1986) and exponential GARCH model of Nelson (1991), each of them with normal and SU-normal distribution (Johnson, 1949a; Johnson, 1949b). It leads us to four models from which we choose the model that does not display autocorrelation and conditional heteroscedasticity indicated by the Escanciano et al. (2009) test. If more suitable models remain, we report a preferred specification according to the Bayesian information criterion (BIC).

Estimating individual models allows us to observe market-level heterogeneities. On the other hand, the realized volatilities of developed stock markets will be cross-correlated due to common global factors. Therefore, we also estimated the model as a dynamic panel using the Dynamic common correlated effect model according to Chudik et al. (2015).

Our event variables related to key interest rate announcements captures the following information:

- volatility 5-days before, at, and 5-days after the news announcement
- a variance of analysts' estimates of the target rate
- negative and positive surprise on the day of the announcement
- volatility one day after the announcement
- volatility 5-days after the announcement with respect to magnitude and direction of the surprise
- international development of target rates
- local monetary policy indication of quantitative easing
- international monetary policy on quantitative easing

As control variables, we used other relevant events that may influence the market volatility level on a given day. It includes, for example, the difference in short-term interest rate, a logarithmic difference of an effective exchange rate, or day-of-the-week effects.

3.1.3 Results

The time series of realized volatility for all the stock markets exhibit similar time patterns with increased volatility during the financial and debt crises. The volatility's logarithmic transformation helped eliminate the skewness in the time series. Moreover, as is often the case in the finance literature, realized volatility shows a high level of persistence which supports our choice for modeling volatility via an autoregressive model: the DHAR-GARCH model.

We first evaluate the results across all markets because the rate announcements and quantitative easing announcements are relatively rare, and the per-market estimators may not have the proper power to detect changes in realized volatility. We utilize two aggregation techniques: the dynamic common correlated error (DCCE) model and the simple mean group (MG) estimator.

Before the news announcement, increased uncertainty of the outcome tends to increase volatility. At the same time, volatility before announcements tends to decrease generally, but the effect is relatively small (approx 1.3% decrease in realized variance). At the news announcement, there was a notable increase in realized variance (approx. 30.5%). The effect is particularly strong when coupled with large surprises. However, the effect of surprises seems to be asymmetric, and a more substantial effect appears when the announced rate is below expectations. Five days after the announcement, estimated volatility declined (approx. 5% decrease in realized variance).

When foreign central banks make announcements, our estimates suggest that volatility increases slightly before and on the news announcement days. After a news announcement, volatility tends to decline. These effects, although occasionally significant, are small. Interestingly, news related to quantitative easing led to a slight decrease in realized volatility before and on the day of the announcement but only when reported by the domestic central bank. Conversely, volatility increased if foreign central banks reported initialization or continuation of the QE.

The key results from the individual market-level analysis of our DHAR-GARCH models show that variables RV_{t-1}, $RV_{t-1,t-5}$, and $RV_{t-1,t-22}$ explain the behavior of volatility changes well because they are often significant with strong effects.

It appears that during the five days before the interest rate announcement, most of the time-realized volatility decreases, except for the Japanese, Italian and European markets. However, except for Japan, changes in volatility before news announcements do not appear significant. On the announcement day, we observed that the stock market's volatility increased in all the countries. This finding was expected, and the effects are strong. The coefficients range from a 2.2% (U.K.) to a 9.4% (U.S.) increase in the log of the realized variance compared to the levels of volatility one day before (approx 10.9% and 54.8% of the realized variance, respectively). Volatility five days after the interest rate announcement has not decreased compared to the level of volatility before the event day. Therefore, a monetary policy news announcement appears to affect volatility only on the day of the announcement and not during the period after the announcement. This result is statistically significant for most countries. We also find that surprises matter. However, their effect differs with respect to any given market.

Realized volatility in the stock markets also appears to be increasing during the days when central banks make interest rate announcements in other countries. However, this effect is significant only in the U.K. and Canada. This result is very intuitive. Canada has strong ties to the U.S., and the U.K. has strong ties to the EU; therefore, one would expect these countries to respond to the announcement of foreign central banks. Most likely, Canada is strongly responding to FED announcements, and the U.K. is strongly responding to ECB announcements.

Lastly, we focused on the effect of announcements about quantitative easing. The result is in contrast to the results achieved via the DCCE model. Therefore, it appears that when controlling for common factors, the effect of the QE on market volatility diminishes. We did not observe a significant increase or decrease in volatility after quantitative easing announcements; the only difference was the reaction of the U.S. stock market.

The research provides robust results but still has some limits. Generalizing results in a multicountry study is not easy because each country behaves slightly differently, and the results could be sensitive to the selected sample of countries. Therefore, we analyzed each country separately and also in a panel setting. We used approximately ten years of data, including the financial crisis, the longest available sample from our data sources, and we think it is a reasonable sample. Still, the results could differ and be time-varying for longer or other periods.

3.2 Impact of macroeconomic news, regulation and hacking exchange markets on the volatility of bitcoin

This paper focuses on bitcoin volatility and tries to identify its drivers. Bitcoin is a fully decentralized cryptocurrency with no central authority responsible for its value, and it is not linked to any particular country. These differences distinguish bitcoin from traditional fiat currencies and create a gap in our knowledge about the bitcoin reactions to some fundamental determinants. Despite the endless discussion about the nature of bitcoin, most research papers agree that bitcoin is not a currency or a long-term investment. However, it should be viewed as a form of speculative, high-risk investment.[2]

2. See, e.g., Yermack (2013), Kristoufek (2013), Bouoiyour; Selmi (2015), Cheah et al. (2015), Bouoiyour; Selmi, et al. (2016), Ciaian et al. (2016), Corbet; Lucey, et al. (2019), Baur; Dimpfl (2018), Baur; Hong, et al. (2018), Smales (2018), Symitsi et al. (2019), Shahzad et al. (2019), Kliber et al. (2019), and Charfeddine et al. (2019)

Table 4: Paper Information and Author Contribution

Reference
Lyócsa, Š., Molnár, P., Plíhal, T., & Širaňová, M. (2020).
Impact of macroeconomic news, regulation and hacking exchange markets on the volatility of bitcoin.
Journal of Economic Dynamics and Control, 119, 103980.

Journal Rankings 2020	**Citations**
WoS AIS: 1.062 (Q2)	WoS: 19
WoS IF: 1.588 (Q3)	Scopus: 19
	Scholar: 45

My Contribution (25%)
Conceptualization, Methodology, Data curation, Investigation, Writing - original draft, Writing - review & editing

Note: Author contribution stated as percentage share and specified using CRediT author statement by Elsevier. Citations were collected in August 2022 and included self-citations.

Extensive research has been done to identify the main factors influencing bitcoin price formation. The main drivers of bitcoin price include:

- the interaction between supply and demand (Ciaian et al., 2016)
- market microfundamentals (e.g, the velocity of bitcoin, the exchange trade ratio) (e.g., Kristoufek, 2013; Bouoiyour; Selmi, 2015; Bouoiyour; Selmi, 2017)
- the price of gold and attention paid to bitcoin news (Bouoiyour; Selmi, 2017)
- market sentiment (Cretarola et al., 2017)
- the network hash rate (e.g., Kristoufek, 2013; Ciaian et al., 2016; Bouoiyour; Selmi, 2017)
- news about regulatory actions (Auer et al., 2018)
- global financial development, oil prices, and the EUR/USD exchange rate (Wijk, 2013)
- output as an important long-term factor (Kristoufek, 2013)
- news related to unemployment and durable goods associated with bitcoin returns (Corbet; Larkin, et al., 2018)

We fill the gap in the literature by studying the role of a broad set of macroeconomic news announcements on the bitcoin price volatility and its jump component. We divide the scheduled macroeconomic news announcements into eight categories. Moreover, we explore news related to regulation, sentiment, and hacking of exchange markets.

3.2.1 Data

Our dataset contains 2152 observations from January 2013 until December 2018. We collected several types of data representing, for example, bitcoin volatility, macroeconomic news announcements, news and sentiment related to the cryptocurrency market, and security breaches of cryptocurrency exchanges. Our data contains entire calendar days, including weekends, and are synchronized to the UTC timezone.

Bitcoin volatility is calculated from BTC/USD individual trades from the Bitstamp exchange. The recent advances in financial econometrics have led to the development of many volatility estimators. Moreover, because we have data for individual trades, it enables a wide range of sampling frequencies and schemes (calendar or business sampling). The actual data generating process is unknown. Therefore, we follow the advice of Patton; Sheppard (2009) and create a simple average of different estimators and sampling frequencies.

In total, we used four volatility estimators:

- standard realized variance that is defined as the sum of intraday squared returns
- first-order adjusted realized variance that controls for first-order serial dependence in intraday returns (French et al., 1987; Patton; Sheppard, 2009; Liu et al., 2015)
- the bipower estimator of Barndorff-Nielsen; Shephard (2004) that leads to consistent estimates in the presence of jumps
- the median realized variance estimator of Andersen; Dobrev, et al. (2012) that also accounts for jumps in the price process, which is likely in the highly volatile bitcoin time series

We use seven different frequencies for calendar and business sampling for each estimator. Our final volatility estimator is then calculated as a simple average of these values. We also analyze the jump component of volatility estimated according to Andersen; Dobrev, et al. (2012) as the difference between the realized variance and its continuous component.

Logarithmic transformation is applied to all our volatility estimators, jump, and continuous components. It is a common practice in the literature, leading to a more symmetric distribution that is much closer to the normal distribution than the raw realized volatility series, which is more suitable for standard time-series modeling purposes, e.g., autoregressive volatility models (Taylor, 2017; Andersen; Bollerslev; Diebold; Ebens, 2001; Andersen; Bollerslev; Diebold; Labys, 2003; Andersen; Bollerslev; Diebold, 2007).

Macroeconomic announcement data are collected from Bloomberg. In total, we used 34 different news divided into eight categories (real economic activity, household consumption decisions, firm investment decisions, government finances, external balances, price evolution, monetary policy decisions, and forward-looking). We focus only on the news related to the US economy because the exchange rate for bitcoin is usually quoted against the US dollar. We build our database based on relevant studies focusing on the effect of US macroeconomic news. The existing literature also consistently reports that US macroeconomic announcements often have a stronger impact on the behavior of asset prices than national surprises (e.g., Andersen; Bollerslev; Diebold; Vega, 2003; Jaggi et al., 2016).

Macroeconomic news announcements are represented by dummy variables that indicate the date of the announcement. Because all our news is scheduled, it was known in advance that some announcement happened on this date. To decrease the number of parameters in the model, we decided to aggregate the information about news announcements for each category. Our created variable measures how many news announcements from each category happen daily from the total number of possible announcements. These variables help us to answer the research question of whether the volatility of the bitcoin price series reacts to economic fundamentals or if its behavior is unrelated to the condition of the US economy.

Cryptocurrency markets tend to react to news related to possible regulatory actions (Auer et al., 2018) and cybercrime events related to the hacking of cryptocurrency exchanges. Therefore, we control for these effects in our model using Financial Times articles, Google Trends sentiment, and recorded days of hacking attacks on cryptocurrency exchanges. We manually selected the most important news from the Financial Times related to bitcoin regulation. We used the ProQuest newspaper database and ended up with 55 news for the period from January 2013 to December 2018. We recorded the date when the authorities or journalists discussed the regulatory action from each news item, and we used three dummy variables to capture the event. To control for possible information leakage and lagged effect, we also created a dummy variable for one day before and one day after the article release date.

Several recent studies have used volume data from Google searches to explain behavior in the bitcoin exchange market (Kristoufek, 2013; Garcia et al., 2014; Cheah et al., 2015; Urquhart, 2018; Aalborg et al., 2019). We used a similar methodology to estimate general sentiment about cryptocurrencies divided into three categories: cryptocurrency supporting sentiment, neutral, and nonsupporting sentiment. To obtain daily data for such an extended period, we follow the method used by Bijl et al. (2016) and N. Kim et al. (2019): we apply a rolling window and calculate the standardized Google Trends (SGT) value.

Cryptocurrency cyber attacks were retrieved from Hackmageddon website [3]. According to Corbet; Cumming, et al. (2019), suspicious price behavior on cryptocurrency exchanges occurs prior to the announcement of hacking. Therefore, we create a variable $Hack_t$ that equals the percentage of the estimated loss from the total market capitalization of bitcoins for the day of the official announcement of the hacking and one day prior, 0 otherwise.

The last control variables are related to bitcoin derivative contracts. The first is the linear time trend, which captures the long-term effect of the changing volatility. The second is a linear time trend, which returns a value of 0 prior to 10 December 2017, thus prior to the introduction of derivatives on the CBOE and CME (18 December 2017), and a time trend value of 1 for 11 December 2017, 2 for 12 December 2017, etc.

3.2.2 Methodology

Our model is based on the standard realized volatility heterogeneous autoregressive model of Corsi (2009). Even though this model is not a long memory in nature, it is known to capture the long memory property of the time series well. Its outstanding relative performance was used in studies from, e.g., Trucíos (2019), Chan et al. (2018), and Lyócsa; Molnár; Plíhal (2019). Another possible alternative is some GARCH class model that was also often used for modeling bitcoin volatility (e.g., Chu et al., 2017; Katsiampa, 2017; Conrad et al., 2018; Baur; Dimpfl; Kuck, 2018). However, we choose to stick with the HAR model because adding other regressors and estimating the model is easy, which makes it more suitable for our analysis.

Our full model specification with all control variables looks as follows:

3. https://www.hackmageddon.com/category/security/cyber-attacks-timeline/

$$
\begin{aligned}
RV_t = & \beta_1 + \beta_2 RV^D_{t-1} + \beta_3 RV^W_{t-1} + \beta_4 RV^M_{t-1} + \\
& RV^D_{t-1} \times (\delta_1 FTN_{t-1} + \delta_2 FTN_t + \delta_3 FTN_{t+1}) + \\
& RV^D_{t-1} \times (\delta_4 NosT_{t-1} + \delta_5 NeuT_{t-1} + \delta_6 SupT_{t-1}) + \\
& RV^D_{t-1} \times \delta_7 Hack_t + \delta_8 Trend_t + \delta_9 Trend_t \times I(t > 10^{th}\ Dec\ 2017) + \\
& RV^D_{t-1} \times \sum_{i=1}^{8} \gamma_i D_{i,t-1} + \epsilon_t
\end{aligned}
\tag{3.4}
$$

RV_t is a realized volatility in day t that we are trying to explain. RV^D_{t-1}, RV^W_{t-1}, RV^M_{t-1} are the components of the standard HAR model and represent are average volatilities over the past day, week, and month. All RV variables are in logarithmic form. FTN_{t-1}, FTN_t, FTN_{t+1} are variables related to Financial Times articles. $NosT_{t-1}$, $NeuT_{t-1}$, and $SupT_{t-1}$ stand for non-supporting, neutral, and supporting sentiment respectively. $Hack_t$ represents hacking attacks, and $Trend_t$ are two trend variables. The parameters of interest are $\gamma_i, i = 1, 2, ..., 8$, which correspond to the effect of the macroeconomic news announcement on the volatility of bitcoin. Specifically, the γ_i coefficients indicate how the next day's volatility, at time t, is anticipated to change if a given (i^{th}) macroeconomic news item is announced on the next day.

Compared to the standard HAR model, our specification uses an interaction of the lagged realized volatility with non-volatility components. We are motivated by our expectation that the effect of the news announcement and other non-volatility variables might differ concerning the current level of market volatility. Therefore, the interaction estimates changes in the next day's volatility relative to the previous day's level of volatility.

Our second model follows the same structure, but we replaced all RV variables on both sides of the equation with the jump component of volatility JC. It allows us to focus only on the jump component of volatility and provide evidence of how it is affected by news announcements. Both models are estimated via OLS with heteroskedasticity and autocorrelation corrected standard errors (Newey et al., 1994).

Moreover, we estimate both models using the non-crossing quantile regression approach because volatility drivers' absolute and relative importance might differ across bitcoin volatility (jump component) distribution quantiles. The models are estimated using the procedure described in Bondell et al., 2010 and considering quantiles $0.05, 0.25, 0.50, 0.75, 0.95$.

3.2.3 Results

As a first step, we checked the bitcoin descriptive statistics and characteristics of its time series. Bitcoin exhibited an unprecedented rise and subsequent fall from the end of 2017 until the end of our series in 2018. Moreover, bitcoin volatility peaked earlier in 2013, when relative price changes were more significant. The average value of annualized realized volatility of bitcoin is 8.529 in our sample. It corresponds to an annualized standard deviation of 71.12%. For example, Bollerslev; Hood, et al. (2018) reports levels of annualized standard deviation for commodities at 25.40%, equities at 20.60%, fixed income at 3.10% and foreign exchange at 10.30%. It indicates that bitcoin is a highly risky asset with enormous volatility compared to other assets. We also found a strong long-memory property for bitcoin volatility time series even at the lag 100. Therefore, our selection of the HAR model seems to be reasonable.

The persistence of the main HAR components does not seem to change substantially across quantiles except for the monthly component, which shows higher coefficients for lower quantiles. The overall level of volatility has not changed over time. However, the volatility in lower quantiles increased, and on the other hand, volatility in higher quantiles decreased. Moreover, introducing derivatives has only led to an increase in the extreme quantiles of volatility distribution. Financial Times article effects also provide statistically significant results. One day after the publication of selected news, the volatility rises quite substantially (by 1.9%), and the effect is almost two times stronger on lower quantiles of volatility. Google Trends sentiment and hacking attacks. Hacking attacks can potentially increase volatility, especially in the higher quantiles. The substantial difference between coefficients in high and low quantiles suggests that cryptocurrency hacking events have the potential to lead to periods of extremely high volatility. Lastly, neutral sentiment, which can be interpreted as general attention, increases the overall level of realized volatility. A similar effect is observed for the supporting (positive) sentiment. The results across quantiles show that the effects tend to increase for extreme quantiles.

For our main variables of interest, macroeconomic announcements, we find that only releases of forward-looking components tend to increase realized volatility of bitcoin. This finding is not surprising because most empirical studies highlight the speculative nature of bitcoin, which is more sensitive to exogenous market disturbances (crashes, regulations) or factors influencing its use as a medium of exchange in black market transactions and tax avoidance. Our results support the hypothesis that bitcoin volatility does not react to macroeconomic news announcements in an economically substantial way.

However, the statistically significant link between bitcoin volatility and specific forward-looking macroeconomic announcements might suggest a potential for a more fundamental role of bitcoin rather than it being a purely speculative asset. Alternatively, as bitcoin currently does not entirely fulfill the role of a medium of exchange in the real economy (Horra et al., 2019), its future utility for transaction purposes will derive from its exchange rate with a widely accepted medium of exchange, the US dollar. Hence, investors wishing to exchange bitcoin for this international currency will ultimately need to incorporate the arrival of new, forward-looking information into their decision-making process.

We also repeated the analysis for the jump component of realized volatility to better understand the drivers of the most rapid changes in bitcoin volatility. The results for control variables are often similar to what we found when analyzing realized volatility. One of the most exciting results is the effect of news related to the regulation of cryptocurrencies and the hacking of cryptocurrency markets on volatility. The effect of these events on the jump component is slightly larger than in the case of volatility, but we expected a more substantial result. Surprisingly, the effect of news articles related to regulation is the same across quantiles, i.e., it does not increase the expected extreme levels of the jump volatility component. The effect of hacking events is also confirmed for jump components which clearly shows that it might be one of the main drivers of the jump component. Therefore, it should not be omitted when evaluating the general risks associated with investments in cryptocurrencies. The results for macroeconomic news announcements are broadly in line with those found for overall volatility.

Moreover, we find a partial significance for government spending in higher quantiles of volatility distribution. As before, the size of the coefficients suggests that the overall effect is somewhat smaller. We, therefore, conclude that macroeconomic news has a limited effect on the volatility process of bitcoin.

To summarize our results, volatility and its jump component seem to be driven primarily by bitcoin-specific risk factors: regulation and hacking attacks on cryptocurrency markets. Unlike traditional assets, bitcoin is almost uninfluenced by general macroeconomic news, thus leading us to the conclusion that bitcoin is only weakly connected to the overall economy via the forward-looking component.

The main limit of our analysis is probably the inclusion of macroeconomic news announcements only from the United States. It was an inevitable choice that helped to keep the number of variables in the models manageable. Moreover, we had reasonable arguments for this choice supported by the academic literature.

4 Realized Volatility Reaction During Crises

The last two papers address two recent crises. The first paper is related to the COVID-19 pandemic and the reaction of the stock markets around the world to government actions. The second paper analyzes intraday investor attention during the beginning of the Russian invasion of Ukraine in early 2022.

4.1 How to calm down the markets? The effects of COVID-19 economic policy responses on financial market uncertainty

Table 5: Paper Information and Author Contribution

Reference
Deev, O., & Plíhal, T. (2022).
How to calm down the markets? The effects of COVID-19 economic policy responses on financial market uncertainty.
Research in international business and finance, 60, 101613.

Journal Rankings 2021	Citations
WoS AIS: 0.695 (Q3)	WoS: 0
WoS IF: 6.143 (Q1)	Scopus: 1
	Scholar: 2

My Contribution (50%)
Conceptualization, Methodology, Software, Visualization,
Writing - original draft, Writing - review & editing

Note: Author contribution stated as percentage share and specified using CRediT author statement by Elsevier. Citations were collected in August 2022 and included self-citations.

This paper focuses on the behavior of the world stock indexes' volatility during the COVID-19 pandemic and their reactions to economic policy actions. The pandemic creates an extreme level of volatility in stock markets last seen more than a decade ago during the global financial crisis (Ali et al., 2020; Baker et al., 2020). Many academic studies have begun to emerge about this topic and analyzed various aspects related to the pandemic, such as the number of cases and fatalities, reproductive number, non-pharmaceutical interventions, investor sentiment, or simply fear.[1]

1. For example: Zhang et al. (2020), Ashraf (2020), Baig et al. (2021), Albulescu (2021), Díaz et al. (2022), Zaremba et al. (2020), Ashraf; Goodell (2021), Bakry et al. (2021), Huynh et al. (2021), and Lyócsa; Baumöhl, et al. (2020)

The effects of the pandemic were devastating. Therefore, governments, central banks, and supervisory authorities worldwide have started an unprecedented amount of policy interventions and responses to support the economy and the financial markets. Since March 2020, governments have intensified their fiscal policy actions to buffer the short-term impact of the COVID-19 economic shock. Many central banks also intervened, decreased interest rates, and provided liquidity injections.

In our paper, we focused on the effect of fiscal, monetary, and macroprudential actions on the realized volatility in 23 countries worldwide. The goal is to analyze the immediate spot market reactions based on high-frequency information and evaluate a possible calming effect of policy actions on the stock markets. Moreover, we measure the spillover impact of US and EU authorities' actions on other markets. To our knowledge, the paper is the first complex study to evaluate the impact of broad government economic actions to relieve the consequences of the COVID-19 pandemic on the stock market's volatility.

Our analysis is broadly related to the literature about the financial implications of the COVID-19 pandemic[2] and the impact of economic policies on stock market risk[3]. We also contribute to the strand of literature focused on the spillover effect by investigating the role of US and EU policy actions for other international stock markets[4].

4.1.1 Data and Methodology

Our analysis focuses on the period from January 2020 to the end of July 2021. We more closely examine two sub-periods. Our main results are based on the period between January and July 2020. The main reason for this sub-sample is the large number of unexpected policy actions during this period and unprecedented levels of volatility. On the other hand, the second selected period (August 2020 - July 2021) consists of a much lower number of announcements mostly related to fiscal policies, volatility stabilizes, and the potential policy actions are more predictable, which lowers uncertainty significantly.

The analyzed dataset consists of the main parts. The first part represents the realized volatility of 8 stock indices from 23 countries worldwide. Volatility data are based on high-

2. Related literature about the financial implications of the COVID-19 pandemic and its regional differences, e.g., Baker et al. (2020), Miescu et al. (2021), J. Wang et al. (2021), Vera-Valdés (2021), Kizys et al. (2021), Demir et al. (2021), Harjoto et al. (2021), Engelhardt et al. (2021), Szczygielski et al. (2021), and Bakry et al. (2021)
3. Related literature with the evidence that macroeconomic measures and announcements have an impact on financial markets, e.g., Caporin et al. (2017), Fiordelisi et al. (2018), X. Huang (2018), Collingro et al. (2020), Bernanke et al. (2005), Heyden et al. (2021), Rahman et al. (2021), Klose et al. (2021), Wei et al. (2021), Yilmazkuday (2021), Bevilacqua et al. (2021), and Pettenuzzo et al. (2021)
4. Related literature about the spillover effects, e.g., Mei et al. (2018), Bekaert; Hoerova, et al. (2013), Miranda-Agrippino et al. (2020), Chen et al. (2016), Yang et al. (2021), and Bevilacqua et al. (2021)

frequency data from the Thomson Reuters DataScope Tick History database provided by Realized Volatility Library from Oxford-Man Institute of Quantitative Finance[5]. The second part of the dataset comprises policy actions and interventions in response to the COVID-19 pandemic from the COVID-19 Financial Response Tracker collected by the Yale Program on Financial Stability (YFPS)[6]. It contains approved actions by central banks, fiscal authorities, and other organizations aimed at restoring financial stability.

We performed our analysis on the heterogeneous autoregressive model (HAR) developed by Corsi (2009) augmented by additional dummy variables representing policy actions. We tried several model specifications, but the most general model could be described as follows:

$$\begin{aligned} RV_{t+1} = &\beta_0 + \beta_1 RV_t^D + \beta_2 RV_t^W + \beta_3 RV_t^M + \\ &\beta_4 RV_t^D \times Act_{t+1} + \beta_5 RV_t^D \times Act_t + \beta_6 RV_t^D \times Act_{t-1} + \epsilon_{t+1} \end{aligned} \tag{4.1}$$

RV stands for the logarithm of 5-minute realized variance, where RV_t^D, RV_t^W, RV_t^M are the components of the basic HAR model that represents past values of daily, weekly, and monthly volatility, respectively. Next, we added the dummy variable Act_t with a value of 1 if any action was announced on a given day or 0 if no actions were approved. The variable Act_{t+1} represents the actions performed one day after the day for which we explain volatility. In other words, it explains what happens with volatility one day before the action takes place. Lastly, Act_{t-1} shows the action declared one day before the day of interest. It is suitable for predictive regression and indicates how the markets reacted the next day after the action was announced.

We add policy actions announcement to the HAR model as interactive terms. All dummy variables in the model are multiplied by (RV_t^D) to control the level of volatility. The model is estimated using ordinary least squares, where standard errors are obtained via heteroskedasticity- and autocorrelation-consistent estimator of Newey et al. (1994).

4.1.2 Results

As a first step, we analyze the policy actions and volatility in individual countries in general. The main components of the HAR model, RV^D, RV^W, and RV^M, play a role of the control variables in our model. The coefficients of the daily and weekly volatility components are positive and statistically significant for almost all countries, which was

5. https://realized.oxford-man.ox.ac.uk/
6. https://som.yale.edu/faculty-research-centers/centers-initiatives/program-on-financial-stability/covid-19-crisis

an expected result due to the high persistence of volatility. Only the monthly component provides a negative coefficient which indicates mean reversion properties. It is caused by the relatively short period accompanied by such a large increase in volatility at the beginning, followed by stabilization and a decrease in volatility. The results for these control variables are pretty stable, and they are not at the center of our attention. Therefore, we do not focus on them in the following analysis.

When we check the effect of action announcements, it is evident that volatility increases during the day of the announcement (Act_t). It is expected because the market tends to react rapidly to new information, and market participants quickly update their positions according to their updated expectations. The most significant effect was observed for the S&P500 index. For the US indexes, there is also evident the calming effect of these policy actions because the volatility decreases significantly during the following day, even more than it increases during the announcement day. The opposite effect was observed in some European countries, namely Belgium, Netherlands, and Norway.

On the other hand, in some counties (India, Japan, Australia), the volatility increases even one day before the announcement day (Act_{t+1}). It could indicate the significance of public discussion on possible policy actions, information leakage before the official announcement, or overall increased policy uncertainty among market participants.

As a next step, we divided policy actions into fiscal stimulus and macroprudential policy. This analysis provides a different picture of Europe and the United States. In Europe, the evidence indicates that the Fiscal Stimulus category is more important than macroprudential policy, and it tends to increase volatility. The stock indexes in the United States show the opposite behavior. There is a significant calming effect of all policy actions on volatility. Still, the macroprudential policy seems to have the most significant impact and helped decrease market volatility the following day after the announcement. The rest of the stock indexes, mainly from Asia and Australia, provide mixed results. In general, our results suggest that the effects of policy action announcements are stronger for developed countries than in emerging markets, where the magnitude of policy effects and their statistical significance tend to be lower.

We also analyzed the spillover effects from the US and Euro area to other countries. We include the additional regressor US Act_{t-1} or EU Act_{t-1} into the baseline model specification. It indicates if some policy action was announced in the US or EU during the previous day. This analysis shows a strong and significant spillover effect of the US policy action announcement that was able to calm the market in most European countries. The majority of other countries seem to be unaffected by the US announcements. On the other hand, the influence of the EU actions on other countries seems minimal and much weaker than the US announcements.

To support our hypothesis that the policy actions announcements had the greatest power during the first few months of the COVID-19 pandemic, we investigate the following one-year period from August 2020 to the end of July 2021. In general, the power of economic policy announcements to affect market uncertainty has decreased significantly. Especially in the United States, the announcements almost lost their ability to influence stock market volatility.

Our findings also explain decreasing and even negative volatility risk premiums in the US in March-April 2020. Government actions in the US decreased the uncertainty, reflected in declining prices of insurance against unexpected volatility (as shown in Cheng, 2020), which subsequently spread to other developed markets. While our findings largely complement previous evidence, we additionally show far greater importance of the macroprudential policy to calm financial markets.

This paper has several limits. It analyzed relatively rare events during a short time period. Even though we performed robustness checks, the results could be sensitive to the selected period. Everything also depends on the quality of the government actions dataset, which slightly changed its methodology during our research and created a challenging task to adjust everything accordingly.

4.2 Russia's ruble during the onset of the Russian invasion of Ukraine in early 2022: The role of implied volatility and attention

Russia-Ukraine relations have been complicated for a long time. The tension between these two countries began to increase in February 2014, following the Ukrainian Revolution of Dignity, also known as the Maidan Revolution. Russia exploited the Ukrainian internal conflicts and subsequently annexed the Crimean Peninsula in February and March 2014, a territory still (as of March 2022) internationally recognized as part of Ukraine. These events were closely followed by a war in Donbas (March 2014), where Russia supported local pro-Russian anti-government separatists in an armed conflict against the Ukrainian government forces (Mankoff, 2014; Rywkin, 2014; Shelest, 2015; Samokhvalov, 2015).

The whole conflict continued and escalated during November and December 2021 when Russia started to increase its military troops near Ukrainian borders. On February 21, 2022, Russian President Vladimir Putin announced that Russia recognized the independence of two pro-Russian regions, Donetsk and Luhansk, in eastern Ukraine. It

Table 6: Paper Information and Author Contribution

Reference
Lyócsa, Š., & Plíhal, T. (2022).
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Finance Research Letters, 102995.

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WoS AIS: 1.245 (Q2)	WoS: 0
WoS IF: 9.848 (Q1)	Scopus: 1
	Scholar: 2

My Contribution (50%) - Corresponding author
Conceptualization, Data curation, Visualization, Investigation, Writing - original draft, Writing - review & editing

Note: Author contribution stated as percentage share and specified using CRediT author statement by Elsevier. Citations were collected in August 2022 and included self-citations.

triggered the first round of economic sanctions from NATO countries in the following days. The whole situation escalated on February 24, 2022, when Russia began a complete invasion of Ukraine, which led to a full-fledged war that surprised most of the global population. As a result, the economic sanctions from other countries against Russia become even more severe. It included, for example, restrictions on Russian imports and exports, the removal of selected Russian banks from the SWIFT interbank system, and the prohibition of the Central Bank of Russia from access to foreign exchange reserves[7].

The war and economic sanctions have dramatically impacted the Russian ruble. It significantly weakened and lost almost 50% of its value against the USD over a few days at the end of February and the beginning of March in 2022. Volatility is a crucial parameter for valuing assets with uncertain future payoffs. In such a turbulent period, an accurate volatility model is in demand by institutional investors and policymakers to understand the value of assets that are tied to the value of the Russian ruble. Based on the existing literature, we hypothesize that we can create a suitable prediction model based on i) limited attention theory and ii) the forward-looking nature of option contracts. More specifically, in this study, we are interested in predicting intraday price fluctuations of the ruble against the USD and the EUR during the onset of the Russo-Ukrainian crisis using the population's attention and investors' expectations.

7. A comprehensive list of all sanctions can be found at https://graphics.reuters.com/UKRAINE-CRISIS/SANCTIONS/byvrjenzmve/

Our research contributes to the academic literature in three ways. First, we contribute to the emerging literature about the effects of the Russian invasion on the financial markets by analyzing the period from the 1^{st} of December 2021 to the end of the 7^{th} of March 2022. Therefore, we expand on existing literature about this very scarce topic so far (e.g., Halousková et al., 2022; Mamonov et al., 2021; Ozili, 2022; Polyzos, 2022).

Second, we contribute to the literature on limited attention theory (Barber et al., 2008) that uses Google Trends data to predict future price variation (Goddard et al., 2015; Dimpfl et al., 2016; Audrino et al., 2020; Lyócsa; Molnár; Plíhal; Širaňová, 2020). We construct our attention measure based on Google searches because it is a good proxy for information demand (Bleher et al., 2021), it is prevalent in many parts of the world and well established in finance literature (e.g. Da et al., 2011; Dimpfl et al., 2016; Audrino et al., 2020; Lyócsa; Molnár; Plíhal; Širaňová, 2020). We extend the current literature to address whether limited attention theory also manifests in intraday trading. Using the intraday measures of attention, unique in the literature, we show that high-frequency attention is still valuable for predicting fluctuations in intraday prices.

Third, we use the information contained in the forward-looking implied volatility and measure its forecasting abilities during such an unexpected crisis. The link between implied volatility's information content and future realized volatility in the foreign exchange market was examined in many previous studies, e.g., Canina et al. (1993), Poon et al. (2003), Gonzalez-Perez (2015), and Plíhal et al. (2021). We apply a novel approach that uses intraday implied volatility of USD/RUB and EUR/RUB. Our results demonstrate that intraday investors' expectations drive intraday realized price fluctuations, and we also provide strong evidence that the implied volatility likely encompasses investors' attention.

4.2.1 Data and Methodology

Our sample of data starts on the 1^{st} of December 2021 and ends on the 7^{th} of March 2022. In early December, the first signs of this threat were publicly recognized by the White House[8], which attracted considerable attention by the media. The selected end of the sample was the most recent data available before the start of this research.

We focused on USD/RUB and EUR/RUB currency pairs. Our exchange rate prices and implied volatility data were retrieved from Bloomberg in a 5-minute frequency. Implied volatilities are extracted from OTC (over-the-counter) forex options with one-month maturity directly quoted on Bloomberg by institutional investors. Because the

8. see an article from the 1^{st} of December 2021, https://www.theguardian.com/world/2021/dec/01/us-warns-russia-plans-large-scale-attack-o n-ukraine.

implied volatility data in such high frequency did not provide enough variation for appropriate analysis, we created six 4-hour intraday windows. For each 4-hour window, realized volatility is calculated as the sum of squared 5-minute returns, and the average of 5-minute implied variance represents implied volatility during the selected 4-hour window. Both volatilities were annualized and synchronized to the UTC (Coordinated Universal Time) time zone.

We use Google Trends as a measure of attention, which is consistent with the increasing number of studies that suggest that attention might drive stock market activity (e.g., N. Kim et al., 2019; Bleher et al., 2019; Lyócsa; Baumöhl, et al., 2020; Aslanidis et al., 2022). Google publishes search volume indices representing the relative popularity of a search term(s) within a given period and across multiple search terms. To capture the population's attention, we retrieve various terms related to the events surrounding the Russo-Ukrainian war. Each term is retrieved separately with no geographical restriction.

To process the Google trends data and create a continuous time series of the same scale, we use the set of procedures according to Kristoufek (2015) and Bleher et al. (2021). We specified three categories of search terms: i) general financial market (e.g., SP 500, VIX, FX market,...), ii) ruble (e.g., ruble, USD rub, Russian interest rate,...), and iii) Russian economy-related (e.g., economic sanctions, asset freeze, Nord Stream 2, export controls, British Petroleum Russia, Ikea Russia,...).

We select the heterogeneous autoregressive volatility (HAR) model of Corsi (2009) and adjust it to our specific needs. The standard HAR model is designed to forecast daily volatility by lagged daily, weekly, and monthly average volatility values. [9] Our research design is characterized by an intra-day approach and a limited sample size. Therefore, we have to adjust the baseline HAR model accordingly.

Due to our limited sample size, we removed weekly and monthly volatility patterns from the model. The model is estimated in log-log form because the onset of the crisis is likely to cause a non-linear response in the market behavior. Moreover, we also consider a specification with the first differences of implied volatilities to count for a possible unit-root-like behavior of implied volatility in our sample.

We have to account for the serial dependence of the volatility series and the possible intraday seasonality. To achieve this, we introduce a dummy variable $I_t(j)$ that takes a value of 1 if the next period of variation belongs to intraday trading window j and 0 otherwise, for $j = 1, 2, ..., 6$.

9. An alternative is to use a generalized autoregressive conditional heteroscedasticity (GARCH) model of Bollerslev (1986). Given the limited sample size, the maximum likelihood estimation of an over-parametrized GARCH class model is not recommended.

A few days before and after the Russian invasion of Ukraine, the amount of relevant news increased considerably, making it impossible to account for specific effects. To account for this issue, we select a period from the 21^{th} to the 28^{th} of February 2022, when the most events occurred. The dummy variable $I_t(q)$ takes a value of 1 if the next given intraday period price variation falls to the day q and 0 otherwise.

In total, we used seven model specifications. The most general model with all our variables was specified as follows:

$$\begin{aligned} lnV_t = &\beta_0 + \beta_1 lnV_{t-1} + lnV_{t-1}\sum_{j=1}^{5}\gamma_j I_t(j) + lnV_{t-1}\sum_{q=1}^{6}\lambda_q I_t(q) + \\ &\eta_1 lnG_{t-1} + \eta_2 lnR_{t-1} + \eta_3 lnE_{t-1} + \pi_1 \Delta lnIV_{t-1} + \pi_2 lnIV_{t-1} + \epsilon_t \end{aligned} \tag{4.2}$$

V_{t-1} stands for realized volatility for a 4-hour window. Interaction terms $\gamma_j lnV_{t-1}I_t(j)$ and $lnV_{t-1}\lambda_q I_t(q)$ corresponds to the intraday seasonality and specific day effects respectively. Lastly $\Delta lnIV_{t-1}$ corresponds to the first difference of implied volatility IV_{t-1}.

The model is estimated via OLS, and the significance of coefficients is derived via the stationary bootstrap method with a block length randomly drawn from the geometric distribution of the expected value, as suggested by the procedure of Politis et al. (2004), Patton; Politis, et al. (2009), and Racine et al. (2021). After each model, we check for the presence of the serial dependence of residuals using the test found in Escanciano et al. (2009).

4.2.2 Results

We provide early evidence on the effects of the imposed economic sanctions and the conflict in the relevant foreign exchange market. Our data showed how the Russian ruble weakened tremendously after the invasion started. This weakening was accompanied by increased price fluctuations and attention to the ruble. Moreover, these two variables showed a remarkable synchronization during this period. In the following days, attention declined, but price volatility remained quite extreme.

Specifically, we find that more attention is being paid toward: i) the financial market, ii) the Russian ruble, and iii) the relationship between economic sanctions and the Russian economy tends to precede more significant price fluctuations in the foreign exchange market. However, investors' expectations, as given by implied volatility, seem to encompass information from attention measures and even beyond.

These results are similar for the USD/RUB and EUR/RUB exchange rates. However, we find that changing investors' expectations (i.e., changes in implied volatilities) are also relevant for the euro, which indicates the increased sensitivity of this currency pair to short-term changes in expectations. The geographical position of the Eurozone is likely behind this effect, as it is much closer to the epicenter of the conflict compared to the United States.

Finally, we applied several robustness checks, including different lengths of intraday windows, sample period adjustments, or a moving average of our attention measures. Despite minor changes in the estimated coefficients, our main conclusions remained largely unchanged.

While attention measures help explain future price changes, from a practical point of view, their timely implementation is challenging, as search terms are not known in advance, specifically in advance of a yet unknown event. Implied volatility does not suffer from this issue. Our results indicate that during unexpected crisis periods, such as the Russo-Ukrainian war, an accurate model of future price fluctuations should utilize high-frequency quoted implied volatility measures. Such data are available in real-time; their implementation into existing models is straightforward, while they also appear to encompass the information content of attention measures.

The primary limit of this paper is a relatively small dataset. The research reacted to an actual issue and tried to explain what was happening in the real world. Right after the paper's publication, the Russian ruble appreciated dramatically, and this event is not captured in our research. We had enough data to explain only the initial depreciation of the ruble. Still, it could be an interesting extension of this research to include a more extended period and cover different reactions of the exchange rate market.

Conclusion

As we can see, volatility is a diverse and interesting topic that offers a lot of research questions that could help us to understand the behavior of asset prices. This collection of essays presented six published papers on volatility modeling and forecasting divided into three parts, each containing two papers. This section highlights the most important contributions to the academic literature.

The first part focuses on forecasting volatility using implied volatility variables and low-frequency data. It contributes to the literature by showing that implied volatility from options with shorter maturities than one month is highly beneficial for one day ahead realized volatility forecasting. Most current literature used only options with 1-month maturity or the VIX index. We claim that selecting the proper option maturity could influence the forecasting performance and that the 1-month rule of thumb could be misleading. The second paper challenges the assumption that realized volatility calculated from high-frequency data is preferable to low-frequency estimators. We show that this assumption holds but depends on the forecast horizon. For forecast horizons of 5 days or less for most analyzed foreign exchange rates, it is better to use high-frequency data if available. However, for longer forecast horizons, the difference between the two is not statistically significant most of the time, which could save time, effort, and processing power. Also, high-frequency data has to be of a good quality which is an issue for some assets, and our research could provide a guide if it is sufficient to use only daily data.

The third and fourth papers measure the effect of macroeconomic news announcements and other events on realized volatility. The third paper focused on central bank announcements and quantitative easing and the reaction of stock markets of seven developed countries. Our contribution to literature lies in using a realized volatility instead of implied volatility that, as we argue, mechanically declined after the announcement. Moreover, we utilize a multicountry study and analyze several days before and after the announcement and not only the day itself. The fourth paper shed new light on the volatility of bitcoin related to macroeconomic news announcements, news about regulation, or security breaches of major exchanges. We also analyzed not only realized volatility but also its jump component separately to provide more insights into this issue.

The last two papers analyzed the recent COVID-19 crisis and the Russian invasion of Ukraine in early 2022. In the paper related to the virus pandemic, we analyzed stock market indices around the world and the reaction of their volatility to government actions. We were among the first to examine such effects in many countries. We found some evidence that the governments were able to calm down the markets, especially in the United States. We were also on the leading edge of the research literature with the paper about ruble reaction in early 2022. Our focus was on investor attention using data from Google trends. One of the innovations was the use of intraday attention variables and volatility data that was not present in the previous literature.

The presented six papers characterize my past career. In future research, I want to focus more on the volatility applications on specific tasks, such as risk management, by improving the forecasts of expected shortfall metrics. I also started cooperation on a project focused on option pricing, where I am trying to implement my knowledge about volatility behavior, which leads me to more interest in modeling and forecasting implied volatility and utilizing the information contained in it.

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