INFECTIOUS DISEASES-RELATED UNCERTAINTY AND THE PREDICTABILITY OF FOREIGN EXCHANGE AND BITCOIN FUTURES REALIZED VOLATILITY

SISA SHIBA[*,¶], JUNCAL CUNADO[†,||], RANGAN GUPTA[‡,**] and SAMRAT GOSWAMI[§,††]

[*]*Department of Economics, University of Pretoria Private Bag X20, Hatfield 0028, South Africa*

[†]*Department of Economics University of Navarra 20280, Pamplona, Spain*

[‡]*Department of Economics University of Pretoria Private Bag X20, Hatfield 0028, South Africa*

[§]*Department of Rural Studies Tripura University Suryamaninagar 799022, Tripura, India*

[¶]*u20810939@tuks.co.za*

[||]*jcunado@unav.es*

[**]*rangan.gupta@up.ac.za*

[††]*sam449@gmail.com*

Published

This paper examines the forecasting power of daily infectious disease-related uncertainty in predicting the realized volatility of nine foreign exchange futures and the Bitcoin futures series using the heterogeneous autoregressive realized variance model. Our results indicate that the infectious diseases-related uncertainty index plays a crucial role in predicting the future path of foreign exchange and Bitcoin futures realized volatility in all the selected time intervals. These findings have important implications for portfolio managers and investors during periods of high levels of uncertainty associated with infectious diseases.

Keywords: Infectious diseases-related uncertainty; foreign exchange market; Bitcoin; realized volatility; forecasting.

JEL Classifications: C22, F31

1. Introduction

The recent COVID-19 outbreak has led to tremendous interest in understanding the "safe haven" nature of the foreign exchange and cryptocurrency markets (see, for example, Fasanya *et al*., 2021; Ji *et al*., 2020; Mnif *et al*., 2020), prompting questions on whether these financial assets class can be considered attractive for investment risk management, financial instruments pricing and strategic asset allocation during a period of infectious diseases-related uncertainty.

Given global financial and economic turmoils, such as the COVID-19 pandemic, markets' hedging strategies that usually work under normal market conditions are likely to fail, leading to extreme market volatility due to high trading activity (see, for example, Harjoto *et al*., 2021; Mazur *et al*., 2021; Ashraf, 2021; Aslam *et al*., 2020; Umar and Gubareva, 2020). In fact, the COVID-19 pandemic triggered an unprecedented level of uncertainty in the financial markets and the global economy (Allen and McAleer, 2021; McAleer, 2021; Salisu *et al*., 2022). However, the reaction of financial assets to this recent crisis was not identical across markets (Arfaoui and Yousaf, 2022; van Der Westhuizen and Aye, 2022). Conlon and McGee (2020), for example, argue that the cryptocurrency market could not be considered a "safe haven" for S&P 500 amid COVID-19 in the short run because of investors' fear and panic. However, the cryptocurrency market was not heavily affected by COVID-19 because it is not so connected to traders' rational behavior, fundamental economic values or central banks, hence, during a time of uncertainty they provide financial stability by reducing financial risks (Caferra and Vidal-Tomás, 2021). Nevertheless, during the COVID-19 shock, there was an increase in the dynamic correlation between Bitcoin and traditional financial markets (Corbet *et al*., 2020). With the increasing popularity of Bitcoin as a new digital asset, an identification of factors that may enhance the predictability of Bitcoin volatility is important (Corbet *et al*., 2018).

As reported in the Triennial Survey of global foreign exchange market volumes of the Bank of International Settlement (BIS), the daily trades in the foreign exchange markets amounted to $6.6 trillion in 2019 and $5.1 trillion three years earlier. However, the rapid spread of COVID-19 confirmed cases in 2020 and the adopted government policies to contain its spread significantly raised exchange rate volatility (Feng *et al*., 2021). As the largest and most liquid market on earth, accurate forecasts of the foreign exchange market are extremely important for investors and policymakers. In addition, accurate forecasting for policymakers is required because exchange rate volatility negatively impacts economic activity[1] (Clark *et al*., 2004; Asteriou *et al*., 2016; Senadza and Diaba, 2017), and hence, high-frequency forecast

[1] Exchange rate volatility affect growth through the following main channels, interest rate, trade and inflation (see Morina *et al*., 2020; Ramzan, 2021).

of the volatility of this market would allow policy authorities to design timely policies in advance by feeding such information into models of now casting for slow-moving macroeconomic aggregates (Bańbura *et al*., 2011). Contemporarily, the perspective of the global financial cycle channel by Adekoya and Oliyide (2021) should be taken into consideration in this regard. Amid the COVID-19 pandemic, the foreign exchange market reacted, see Bazan-Palomino and Winkelried (2021). However, the reaction of most central banks to adjust monetary frameworks as a response to the crisis (Padhan and Prabheesh, 2021) played an important role in ensuring the quick recovery of the foreign exchange market as they are directly affected by monetary policy (Kartal *et al*., 2021; Baker *et al*., 2020a). Also, governments' rapid response toward containing the spread of the virus played an important role in guaranteeing stability in financial markets in the presence of the pandemic (Zaremba *et al*., 2021).[2] Following the coronavirus pandemic, the volatility in the financial markets attracted a number of practitioners and researchers to search for safe-haven assets (see, for example, Shiba *et al*., 2022; Gupta *et al*., 2021; Bouri *et al*., 2020). Pong *et al*. (2004), Rapach and Strauss (2008), Christou *et al*. (2018) and Liu *et al*. (2020) used the univariate and multivariate versions of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and the multifractal models in forecasting exchange rate volatility.

In the context of the existing literature, our paper is the first to empirically examine the forecasting ability of uncertainty related to daily infectious diseases (EMVID) in predicting the realized volatility of foreign exchange and Bitcoin futures using the heterogeneous autoregressive realized variance (HAR-RV) model. The choice of cryptocurrency Bitcoin is for comparison with traditional currency-based exchange rates, and also due to its rapid growth in recent times as an investment vehicle.[3] Specifically speaking, it accounts for 42% of the total market share of cryptocurrencies (see: https://coinmarketcap.com). The selected HAR-RV model reproduces most properties of time series data such as fat tails, long memory and self-similarities when forecasting realized volatility (Gkillas *et al*., 2020). The paper attempts to make four main contributions to the related financial market literature. First, we examine infectious diseases-related uncertainty using daily data from as early as January 2000, most importantly, this period includes other infectious diseases like the H1N1 diseases from 2009 to 2010, then the Ebola pandemic that effectively too part in 2014 to 2016. Among other diseases that took place in our period of interest includes the H5N1, MERS and SARS viruses. As a proxy for daily infectious disease-related uncertainty, we employ the

[2] For example, lockdowns, wearing of masks, social distancing and most importantly, the social relief grant that were issued to economic agents.

[3] The cryptocurrencies had a total market value of $3 trillion in November 2021 from $20 billion in 2017. This rapid increase in growth attracted individuals and institutional investors (Iyer, 2022)

newspaper-based index by Baker *et al*. (2020b), that follows the daily equity-market volatility (EMV) in the Chicago Board Options Exchange (CBOE) volatility index. This index is an appropriate measure in the statistical model aimed to forecast the foreign exchange and the Bitcoin futures realized volatility. To ensure precise and accurate forecast and estimation, we employ the intraday data. Second, our paper adds value to the emerging literature of foreign exchange and cryptocurrency markets by predicting their realized volatility computed from 5 min difference using the extended HAR-RV model by Corsi (2009) (i.e., we add the daily EMVID index into the basic HAR-RV model and assess its ability to predict the foreign exchange and Bitcoin futures realized volatility). Third, we evaluate the predictability of EMVID for foreign exchange and Bitcoin realized volatility by considering the short-, medium-, and long-run ($h = 1$, 5 and 22, respectively) out-of-sample approach. Lastly, we focus on the predictability of the EMVID index for foreign exchange and Bitcoin futures realized volatility during the recent COVID-19 shock to observe the response of these asset classes. It is worth noting that this analysis will have important implications for investors and portfolio managers in the foreign exchange and Bitcoin markets.

The structure of the paper is as follows. In Sec. 2, we present the dataset and the HAR-RV model. Section 3 includes the forecasting results for foreign exchange and Bitcoin futures markets. Finally, Sec. 4 concludes.

2. Dataset and Methodology

2.1. *Dataset*

We use intraday realized volatility data of foreign exchange and Bitcoin futures market index provided by Dacheng Xiu from the Risk Lab at Booth School of Business of the University of Chicago. All the data are available at https://dachxiu.chicagobooth.edu/#risklab. The choice of our variables of interest is primarily based on data availability and that they are the major traded foreign exchange rates. In computing intraday realized volatility data, Dacheng Xiu employs quasi-maximum likelihood estimates of a moving average model -MA(q)-. In our analysis, we select the 5 min realized volatility estimates as it contains the most precise and accurate information. Table 1 includes the selected variables (9 exchange rates and the Bitcoin) and their acronyms, as well as their sample period coverages.

We also employ the daily EMVID proposed by Baker *et al*. (2020b) which is available since January 1985 at http://policyuncertainty.com/infectiousEMV.html. To construct EMVID, Baker *et al*. (2020b) implemented a textual analysis based on four terms, namely E: economic, economy, financial; M: "stock market", equity, equities, "Standard and Poor"; V: volatility, volatile, uncertain, uncertainty, risky; ID: epidemic, pandemic, virus, flu, diseases, coronavirus, MERS, SARS, Ebola,

Table 1. Selected variables, acronyms and sample coverage.

Symbol	Future index	Sample period
1. AD	Australian Dollar	22/09/2008–17/06/2021
2. BP	British Dollar	22/09/2008–17/06/2021
3. CD	Canadian Dollar	22/09/2008–17/06/2021
4. JY	Japanese Yen	22/09/2008–17/06/2021
5. JYNM	Japanese Yen E-mini	27/07/2017–17/06/2021
6. NE	New Zealand Dollar	22/09/2008–17/06/2021
7. SF	Swiss Franc	22/09/2008–17/06/2021
8. URO	Euro FX	22/09/2008–17/06/2021
9. UROM	Euro FX E-mini	27/07/2015–17/06/2021
10. BTC	CME Bitcoin	18/12/2017–17/06/2021

H5N1 and H1N1. A daily count of one of the EMVID terms is attributed in the EMVID index from approximately 3000 US newspaper articles. Furthermore, Baker *et al*. (2020b) then multiplicatively rescale the final series to match the VIX level through the EMV index and the EMVID index is scaled to equal the EMV articles. Amid infectious diseases, the EMVID index is the only proxy available for infectious disease-related uncertainty.

The sample periods range from the earliest data available to the date of our estimation incorporating various market events such as the 2008 global financial crisis and the COVID-19 episode.

2.2. *Heterogeneous autoregressive realized variance model*

We conduct the short-, medium- and long-run ($h = 1$, 5 and 22, respectively) out-of-sample predictability using the HAR-RV model proposed by Corsi (2009). The HAR-RV model employs volatility from different time horizons to predict realized volatility of financial assets given trader's different sensitivities to new information (Müller *et al*., 1997) while it satisfies all the important properties of the realized variance on returns (Bonato *et al*., 2021; Wang *et al*., 2019). The benchmark HAR-RV model is given by

$$\mathrm{RV}_{t+h} = \beta_0 + \beta_d \mathrm{RV}_t + \beta_w \mathrm{RV}_{w,t} + \beta_m \mathrm{RV}_{m,t} + \varepsilon_{t+h} \tag{1}$$

where RV is the realized volatility h-days ahead are represented by the h index with $h = 1$, 5 and 22; $\mathrm{RV}_{w,t}$ is the average RV from day $t-6$ to $t-1$ and $\mathrm{RV}_{m,t}$ depicts the mean RV from $t-22$ to $t-6$. We extend the benchmark HAR-RV model in Eq. (1) by adding the EMVID variable to capture the uncertainty index. The extended HAR-RV model is given by

$$\mathrm{RV}_{t+h} = \beta_0 + \beta_d \mathrm{RV}_t + \beta_w \mathrm{RV}_{w,t} + \beta_m \mathrm{RV}_{m,t} + \theta \mathrm{EMVID}_t + \varepsilon_{t+h} \tag{2}$$

3. Empirical Results

Following Campbell (2008), we consider that the performance of any predictability model is captured in its out-of-sample forecasts. The main purpose of this paper is to analyze the role EMVID plays in predicting the future path of foreign exchange and Bitcoin futures realized volatility using the recursive out-of-sample estimation approach from each index's earliest available date to the model's latest estimation date. In determining the HAR-RV model's multiple structural breakpoints tests, we use the UD_{Max} and WD_{Max} statistics initially proposed by Bai and Perron (2003). The detected structural breakpoints are presented in Table 2. The futures index of BP, CD, URO, AD and SF experienced structural breakpoints in 2010. In addition, the structural break for NE was detected in 2011, whereas the JYNM and UROM had a break in 2016 and the JY had a structural break within the COVID-19 period. The Bitcoin index experienced a structural breakpoint in 2018. The time series data under instigation is stationary when we look at the data plot (Fig. A1). Further stationarity test was test using the Augmented Dickey–Fuller unit root test. Through this test, all series were stationary.

Next, we compute the root mean square forecast errors (RMSFEs) for the basic HAR-RV and the extended HAR-RV model in all-time horizons ($h = 1$, $h = 5$ and $h = 22$). Minimal values of the RMSFEs in the out-of-sample forecast will indicate a better performing model, i.e., the model with or without EMVID (see Shiba and Gupta, 2021). For the forecasting accuracy test in our models, we employed the MSE-F test proposed by McCracken (2007). Our out-of-sample forecasting gains (FG) are calculated using

$$\mathrm{FG} = \left(\frac{\mathrm{RMSFE}_0}{\mathrm{RMSFE}_1} - 1\right)100, \tag{3}$$

Table 2. Structural breakpoints.

Structural breaks	Variables
Sep-2010	BP, CD and URO
Oct-2010	AD
Nov-2010	SF
Oct-2011	NE
Jul-2016	JYNM and UROM
Jul-2018	BTC
Mar-2021	JY

Note: Structural breakpoint detected using Bai and Perron (2003).

Table 3. Out-of-sample predictability.

RMSE0	RMSEE 1	FGs	RMSE0	RMSEE 1	FGs
Panel 1: AD. 10/12/2010			Panel 2. BP: 9/14/2010		
0.0304	0.0302	0.8649***	0.0267	0.0257	3.8418***
0.0080	0.0079	1.1801***	0.0071	0.0067	6.1012***
0.0021	0.0018	13.7084***	0.0017	0.0017	3.9133***
Panel 3: CD. 9/14/2010			Panel 4: JY. 3/21/2021		
0.0187	0.0187	−0.0214	0.0293	0.0298	−1.5967
0.0047	0.0047	0.9354***	0.0079	0.0075	4.2624***
0.0008	0.0007	11.7647***	0.0012	0.0012	3.8494***
Panel 5: JYNM. 7/27/2016			Panel 6: NE. 10/18/2011		
0.0442	0.0282	56.4489***	0.0313	0.0306	2.1152***
0.0088	0.0070	25.6597***	0.0084	0.0077	9.5010***
0.0033	0.0018	80.6593***	0.0020	0.0019	0.9824***
Panel 7: SF. 11/04/2010			Panel 8: URO. 9/03/2010		
0.0535	0.0535	0.0168	0.0206	0.0206	−0.0340
0.0139	0.0139	0.0793***	0.0053	0.0053	0.2068***
0.0034	0.0034	0.1170***	0.0014	0.0014	0.2911***
Panel 9: UROM. 7/01/2016			Panel 10: BTC. 7/18/2018		
0.0252	0.0252	−0.1111	0.4375	0.2672	63.7319***
0.0058	0.0057	0.5416***	0.3235	0.0718	350.8863***
0.0018	0.0015	21.2202***	0.0378	0.0182	108.1448***

Notes: $\text{FG} = (\frac{\text{RMSFE}_0}{\text{RMSFE}_1} - 1)*100$ computes the forecasting gains (FG), where the root mean square forecast errors (RMSFE_S) for the benchmark model is represented as RMSFE_0, and the extended model is shown as RMSFE_1. The estimated basic HAR-RV model is given by $\text{RV}_{t+h} = \beta_0 + \beta_d \text{RV}_t + \beta_w \text{RV}_{w,t} + \beta_m \text{RV}_{m,t} + \varepsilon_{t+h}$; and the extended HAR-RV model is given by $\text{RV}_{t+h} = \beta_0 + \beta_d \text{RV}_t + \beta_w \text{RV}_{w,t} + \beta_m \text{RV}_{m,t} + \theta \text{EMVID}_t + \varepsilon_{t+h}$. Daily realized volatility for foreign exchange and Bitcoin futures is denoted as RV and EMVID represents daily infectious disease-related uncertainty. The level of significance as computed by the MSE-F test at 1% level are indicated by ***.

where RMSFE_0 indicates RMSFEs for the benchmark model and RMSFE_1 represents the RMSFEs for the extended model. These results are shown in Table 3 together with their respective FGs. According to our out-of-sample results, the Bitcoin futures index realized volatility presents the highest forecast gain of 350.89% in the $h = 5$-time horizon followed by a 108.14% forecast gain in the $h = 22$-time horizon, whereas the JYNM futures realized volatility observes an 80.66% forecast gain in the $h = 22$-time horizon. Previous empirical evidence suggests that when taking the information context of uncertainty related to infectious diseases based on the daily newspaper-based index into account, we can obtain the highest forecast gain of 350.89% ($h = 5$). The Swiss Franc futures RV

Table 4. Out-of-sample FG for the COVID-19 episode.

RMSE0	RMSEE 1	FGs	RMSE0	RMSEE 1	FGs
Panel 1: AD. 01/02/2019			Panel 2: BP. 01/02/2019		
0.0352	0.0332	6.2477***	0.0232	0.0235	−1.3083
0.0096	0.0083	15.9706***	0.0079	0.0061	29.8627***
0.0024	0.0022	9.8206***	0.0020	0.0017	22.3827***
Panel 3: CD. 01/02/2019			Panel 4: JY. 01/02/2019		
0.0178	0.0181	−1.5015	0.0200	0.0199	0.4278***
0.0045	0.0044	2.2887***	0.0050	0.0049	2.7071***
0.0009	0.0008	9.6031***	0.0010	0.0010	1.4735***
Panel 5: JYNM. 01/02/2019			Panel 6: NE. 01/02/2019		
0.0233	0.0233	0.1889	0.0311	0.0311	0.0322
0.0066	0.0059	12.1827***	0.0092	0.0079	16.8695***
0.0017	0.0016	9.1201***	0.0021	0.0021	1.9580***
Panel 7: SF. 01/02/2019			Panel 8: URO. 01/02/2019		
0.0249	0.0175	42.4267***	0.0151	0.0139	8.3663***
0.0044	0.0043	1.3689***	0.0042	0.0036	17.3039***
0.0033	0.0012	184.7414***	0.0010	0.0010	2.6178***
Panel 9: UROM. 01/02/2019			Panel 10: BTC. 01/02/2019		
0.0191	0.0178	7.0156***	0.4177	0.2659	57.1161***
0.0049	0.0044	13.3074***	0.2626	0.0699	275.6125***
0.0012	0.0012	4.4351***	0.0354	0.0182	94.7235***

Notes: In the COVID-19 period, the forecast gains are computed as follows, $\mathrm{FG} = (\frac{\mathrm{RMSFE}_0}{\mathrm{RMSFE}_1} - 1)*100$ the root mean square forecast errors (RMSFE_S) for the benchmark model (Eq. (1)) is represented as RMSFE_0, and that of the extended model is shown as RMSFE_1 (Eq. (2)). RV denotes the daily realized volatility for foreign exchange and bitcoin futures. The daily infectious disease-related uncertainty is represented by EMVID. The level of significance is denoted by *** and computed by the MSE-F test.

experienced the lowest FGs of 0.02%, 0.08% and 0.11% in the $h = 1$-, 5- and 22-time horizon, respectively. The Euro FX, respectively, experienced lower FGs of 0.21% and 0.29% in $h = 5$- and $h = 22$-time horizon. This indicates that we can get the lowest forecast gain of 0.02%, 0.08%, and 0.11% in SF futures $h = 1$-, 5- and 22-time horizon when considering the EMVID index amid the RMSFEs forecast accuracy metrics, respectively. In the presence of infectious diseases-related uncertainty, we can acquire a 0.21% and a 0.29% forecast gain in the $h = 5$- and $h = 22$-time horizon, respectively. On the other hand, the CD, UROM and JY futures index experienced forecast loss of 0.02%, 0.11% and 1.60% in the $h = 1$ model, respectively.

Looking at these results, the extended HAR-RV model performs better than the benchmark HAR-RV model. These results are significant at all levels of significance for AD, BP, CD ($h = 5$ and 22), JY ($h = 5$ and 22), JYNM, NE, SE ($h = 5$ and 22), URO ($h = 55$ and 22), UROM ($h = 5$ and 22) and BTC according to the MSE-F test. These findings indicate that the EMVID index plays an important role in forecasting the future path of foreign exchange and Bitcoin in all time horizons.

Finally, for robustness check, we extend our out-of-sample estimation to only cover the COVID-19 episode from January 2020 and aim for the in-sample period to have equal observations (Table 4). This period takes into account all the COVID-19 waves and it allows the reaction of the markets as a response to the policy implementations that were made to contain the spread of the virus. Our recursive analysis approach depicts that the highest forecast gain of 275.61%, followed by 184.74% and 94.72% within the COVID-19 period were evident in BTC ($h = 5$), SF ($h = 22$) and BTC ($h = 22$), respectively. These results suggest that taking infectious diseases-related uncertainty into account, the model presents a 275.61% forecast gain in the $h = 5$ horizon in the BTC index and a 184.74% forecast gain in ST under the $h = 22$ horizon, with a 94.72% FG in the BTC index $h = 22$ model. On the lower bound, the NE has a 0.03% forecast gain in the $h = 1$ model followed by the forecast gain of 0.18% in a JYNM ($h = 1$) and a 0.43% forecast gain in JY ($h = 1$). Considering the RMSFEs forecast accuracy, we can infer a 0.03% forecast gain in NE ($h = 1$) followed by a 0.18% forecast gain in the JYNM $h = 1$ horizon followed by a 0.43% forecast gain in JY under the $h = 1$ horizon.

4. Concluding Remarks

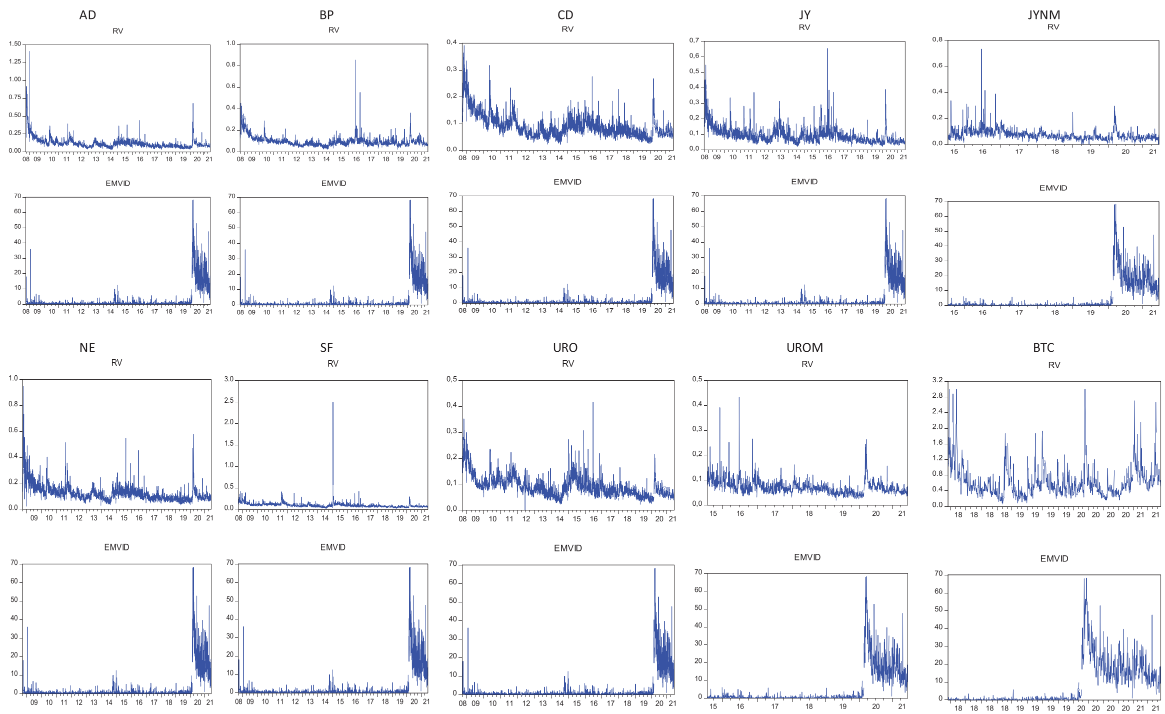
The COVID-19 outbreak prompted questions regarding the "safe haven" nature of foreign exchange and Bitcoin futures. Amid infectious diseases-related uncertainty, especially the recent COVID-19 pandemic, this paper contributes to the literature of foreign exchange and Bitcoin by forecasting their realized volatility by considering a recursive out-of-sample extended HAR-RV model over the short-($h = 1$), medium-($h = 5$) and long-run ($h = 22$) periods. Our findings indicate that EMVID plays a critical role in predicting the future path of foreign exchange and Bitcoin futures realized volatility and these results are significant at all levels of significance. In particular, the Bitcoin futures index had the highest forecast gains followed by the JYNM index. The SF had the lowest forecast gain, while the CD, UROM and JY have forecast losses.

We extended our analysis to assess the COVID-19 episode. The same results were evident. Interestingly, the highest forecast gains were obtained for the case of Bitcoin. This emphasizes the fact that this asset class is not linked to any government, economic fundamental or central bank. Our findings have important implications for investors, portfolio managers and policymakers in their portfolio risk management, strategic asset allocation and financial instruments pricing decisions during periods of high levels of uncertainty resulting from infectious diseases, such as COVID-19. For future studies, we will extend our analysis to assess the impact of the EMVID on food security since the novel virus had a great impact on human health, therefore, human productivity was inversely affected. Also, the economic activity restrictions and lockdowns imposed to contain the spread of the virus had a significant impact in the food supply chain.

Acknowledgments

The authors would like to pass their gratitude to two anonymous referees for their value-adding comments. They also acknowledge that any remaining errors are solely theirs.

Appendix A



Notes: RV depicts the realized volatility of the foreign exchange and bitcoin futures index. EMVID represents the newspaper-based uncertainty index related to infectious diseases.

Figure A.1. Data plots.

References

Adekoya, OB and JA Oliyide (2021). How COVID-19 drives connectedness among commodity and financial markets: Evidence from TVP-VAR and causality-in-quantiles techniques. *Resources Policy*, 70, 101898.

Allen, DE and M McAleer (2021). Predicting COVID-19 cases and deaths in the USA from tests and state populations. *Advances in Decision Sciences*, 25(2), 1–27.

Arfaoui, N and I Yousaf (2022). Impact of COVID-19 on volatility spillovers across international markets: Evidence from VAR asymmetric BEKK GARCH model. *Annals of Financial Economics*, 17(1), 2250004.

Ashraf, BN (2021). Stock markets' reaction to COVID-19: Moderating role of national culture. *Finance Research Letters*, 41, 101857.

Aslam, F, S Aziz, DK Nguyen, KS Mughal and M Khan (2020). On the efficiency of foreign exchange markets in times of the COVID-19 pandemic. *Technological Forecasting and Social Change*, 161, 120261.

Asteriou, D, K Masatci and K Pilbeam (2016). Exchange rate volatility and international trade: International evidence from the MINT countries. *Economic Modelling*, 58, 133–140.

Baker, SR, N Bloom, SJ Davis, KJ Kost, MC Sammon and T Viratyosin (2020a). The unprecedented stock market impact of COVID-19. *The Review of Asset Pricing Studies*, 10(4), 742–758.

Baker, SR, N Bloom, SJ Davis and SJ Terry (2020b). Covid-induced economic uncertainty. NBER Working Paper No. 26983. National Bureau of Economic Research.

Bańbura, M, D Giannone and L Reichlin (2011). Nowcasting. In Clements, MP and DF Hendry (Eds.), *The Oxford Handbook on Economic Forecasting*, pp. 63–90. Oxford University Press, USA.

Bazan-Palomino, W and D Winkelried (2021). FX markets' reactions to COVID-19: Are they different? *International Economics*, 167, 50–58.

Bonato, M, K Gkillas, R Gupta and C Pierdzioch (2021). A note on investor happiness and the predictability of realized volatility of gold. *Finance Research Letters*, 39, 101614.

Bouri, E, R Demirer, R Gupta and C Pierdzioch (2020). Infectious diseases, market uncertainty and oil market volatility. *Energies*, 13, 4090.

Caferra, R and D Vidal-Tomás (2021). Who raised from the abyss? A comparison between cryptocurrency and stock market dynamics during the COVID-19 pandemic. *Finance Research Letters*, 43, 101954.

Campbell, JY (2008). Estimating the equity premium. *Canadian Journal of Economics/Revue canadienne d'conomique*, 41, 1–21.

Christou, C, R Gupta, C Hassapis and MT Suleman (2018). The role of economic uncertainty in forecasting exchange-rate returns and realized volatility: Evidence from quantile predictive regressions. *Journal of Forecasting*, 37(7), 705–719.

Clark, PB, S-J Wei, NT Tamirisa, AM Sadikov and L Zeng (2004). A new look at exchange rate volatility and trade flows. IMF Occasional Paper No. 2004/009. International Monetary Fund, Washington, D.C.

Conlon, T and R McGee (2020). Safe haven or risky hazard? Bitcoin during the COVID-19 bear market. *Finance Research Letters*, 35, 101607.

Corbet, S, C Larkin and B Lucey (2020). The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letters*, 35, 101554.

Corbet, S, A Meegan, C Larkin, B Lucey and L Yarovaya (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165, 28–34.

Corsi, F (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, 7, 174–196.

Fasanya, IO, O Oyewole, OB Adekoya and J Odei-Mensah (2021). Dynamic spillovers and connectedness between COVID-19 pandemic and global foreign exchange markets. *Economic Research-Ekonomska Istraživanja*, 34, 2059–2084.

Feng, GF, HC Yang, Q Gong and CP Chang (2021). What is the exchange rate volatility response to COVID-19 and government interventions? *Economic Analysis and Policy*, 69, 705–719.

Gkillas, K, R Gupta and C Pierdzioch (2020). Forecasting realized gold volatility: Is there a role of geopolitical risks? *Finance Research Letters*, 35, 101280.

Gupta, R, S Subramaniam, E Bouri and Q Ji (2021). Infectious disease-related uncertainty and the safe-haven characteristic of US treasury securities. *International Review of Economics & Finance*, 71, 289–298.

Harjoto, MA, F Rossi and JK Paglia (2021). COVID-19: Stock market reactions to the shock and the stimulus. *Applied Economics Letters*, 28, 795–801.

Iyer, T (2022). Cryptic Connections: Spillovers between Crypto and Equity Markets. Notes No. 2022/01, International Monetary Fund, Monetary and Capital Markets, Global Financial Stability.

Ji, Q, D Zhang and Y Zhao (2020). Searching for safe-haven assets during the COVID-19 pandemic. *International Review of Financial Analysis*, 71, 101526.

Kartal, MT, Ö Depren and SK Depren (2021). Do monetary policy measures affect foreign exchange rates during the COVID-19 pandemic? Evidence from Turkey. *BDDK Bankacılık ve Finansal Piyasalar Dergisi*, 15, 175–202.

Liu, R, R Demirer, R Gupta and ME Wohar (2020). Volatility forecasting with bivariate multifractal models. *Journal of Forecasting*, 39(2), 155–167.

Mazur, M, M Dang and M Vega (2021). COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. *Finance Research Letters*, 38, 101690.

McAleer, M (2021). Critical analysis of some recent medical research in Science on COVID-19. *Advances in Decision Sciences*, 25(1), 1–41.

McCracken, MW (2007). Asymptotics for out of sample tests of Granger causality. *Journal of Econometrics*, 140, 719–752.

Mnif, E, A Jarboui and K Mouakhar (2020). How the cryptocurrency market has performed during COVID 19? A multifractal analysis. *Finance Research Letters*, 36, 101647.

Morina, F, E Hysa, U Ergün, M Panait and MC Voica (2020). The effect of exchange rate volatility on economic growth: Case of the CEE countries. *Journal of Risk and Financial Management*, 13(8), 177.

Müller, UA, MM Dacorogna, RD Davé, RB Olsen, OV Pictet and JE Von Weizsäcker (1997). Volatilities of different time resolutions — analyzing the dynamics of market components. *Journal of Empirical Finance*, 4, 213–239.

Padhan, R and K Prabheesh (2021). The economics of COVID-19 pandemic: A survey. *Economic Analysis and Policy*, 70, 220–237.

Pong, S, MB Shackleton, SJ Taylor and X Xu (2004). Forecasting currency volatility: A comparison of implied volatilities and AR(FI)MA models. *Journal of Banking & Finance*, 28(10), 2541–2563.

Rapach, DE and JK Strauss (2008). Structural breaks and GARCH models of exchange rate volatility. *Journal of Applied Econometrics*, 23(1), 65–90.

Ramzan, M (2021). Symmetric impact of exchange rate volatility on foreign direct investment in Pakistan: Do the global financial crises and political regimes matter?. *Annals of Financial Economics*, 16(4), 1–21.

Salisu, AA, R Gupta and R Demirer (2022). A note on uncertainty due to infectious diseases and output growth of the United States: A mixed-frequency forecasting experiment. *Annals of Financial Economics*, 17(2), 2250009.

Senadza, B and DD Diaba (2017). Effect of exchange rate volatility on trade in Sub-Saharan Africa? *Journal of African Trade*, 4(1–2), 20–36.

Shiba, S, J Cunado and R Gupta (2022). Predictability of the realised volatility of international stock markets amid uncertainty related to infectious diseases. *Journal of Risk and Financial Management*, 15, 18.

Shiba, S and R Gupta (2021). Uncertainty related to infectious diseases and forecastability of the realized volatility of US treasury securities. *Annals of Financial Economics*, 16(2), 2150008.

Umar, Z and M Gubareva (2020). A time-frequency analysis of the impact of the Covid-19 induced panic on the volatility of currency and cryptocurrency markets. *Journal of Behavioral and Experimental Finance*, 28, 100404.

Urquhart, A and H Zhang (2019). Is Bitcoin a hedge or safe haven for currencies? An intraday analysis. *International Review of Financial Analysis*, 63, 49–57.

van Der Westhuizen, C and G Aye (2022). Contagion across financial markets during COVID-19: A look at volatility spillovers between the stock and foreign exchange markets in South Africa. *Annals of Financial Economics*, 17(1), 2250002.

Wang, X, H Liu, S Huang and B Lucey (2019). Identifying the multiscale financial contagion in precious metal markets. *International Review of Financial Analysis*, 63, 209–219.

Zaremba, A, R Kizys, P Tzouvanas, DY Aharon and E Demir (2021). The quest for multidimensional financial immunity to the COVID-19 pandemic: Evidence from international stock markets. *Journal of International Financial Markets, Institutions and Money*, 71, 101284.