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UNCERTAINTY RELATED TO INFECTIOUS DISEASES AND FORECASTABILITY OF THE VOLATILITY OF FINANCIAL ASSETS

by

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Abstract

In the context of the great turmoil in the financial markets caused by the COVID-19 outbreak, we examine the predictability of the US Treasury securities (Chapter 2), international stocks (Chapter 3), foreign exchange rates and Bitcoin (Chapter 4) and agricultural commodity futures (Chapter 5) given daily infectious diseases-related uncertainties (EMVID) using the heterogonous autoregressive volatility (HAV-RV) model. On stationary intraday data computed from a 5-minute interval, we conduct a recursive out-of-sample forecast. Through the RMSFE metric, our results provide evidence that these financial assets remain attractive to investors within the pandemic episode, with Bitcoin obtaining significantly high forecast gains among all the other assets in the medium and long forecast horizons. The US Treasury securities remain risk-free and the worldwide recognition of gold as a "safe haven" asset is emphasised. Among the agricultural traded commodities, cocoa and oats futures had significant forecast gains. The international stocks in Pakistan and Singapore appeared to be the most volatile. It is also evident that an econometrician can acquire the highest forecast gain in the Swiss Franc futures in the foreign exchange market.

In Chapter 6, we use annual data on real gold returns and the probability of fatality due to contagious diseases over the period 1258 to 2020, we detect nonlinearity and regime changes in the relationship between the two variables of concern. We rely on a quantile regression model to show that real gold returns can hedge against the risks associated with such rare disasters (COVID-19), primarily when the market is in its bullish state, with it being negatively impacted in its bearish state.

By assessing the role of contagious diseases on these financial assets' returns we find strong evidence that contagious diseases play an important role in forecasting their RV. Understandably, our results have important portfolio implications for investors, speculators and portfolio managers during periods of high levels of uncertainty associated with infectious diseases.

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Chapter 1

General Introduction

Amid contagious diseases, especially the disastrous COVID-19, we explore the predictive power of daily infectious diseases-related uncertainty on the volatility of US Treasury securities, international stocks, major foreign exchange rate, Bitcoin, agricultural commodities, and gold futures. We are interested at these financial assets classes because, first, the United States (US) securities have a significant lack of default risk as the US government produces approximately 20% of the world's output, making it to have massive revenue streams (Kopyl and Lee, 2016). Also, the US Treasury securities as suggested by Cheema and Szulczuk (2020) are one of the most risk-free and liquid financial assets in the financial market. Second, following the pandemic outbreak, there was a notable negative response in international stock markets' returns (Ashraf 2021, Gao et al. 2021; Lyócsa et al. 2020), the S&P 500[1] and Nasdaq decreased by 4.9% and 4.7%, respectively, also Wang et al. (2020) show that the Dow Jones had a significant drop since 1987.

Third, we look at the foreign exchange rate (FX) market amid COVID-19 as it is the largest and most liquid market in the world[2]. The disconnection of the cryptocurrency market from economic fundamentals (Caferra and Vidal-Tomás, 2021) motivates the investigation of this asset class given the pandemic. Furthermore, the lockdown in the world that resulted from the COVID-19 pandemic caused a great disruption in the food supply chain given our already existing food insecurity (Food Security Information Network 2020)[3]. It is important to investigate specifically the impact the pandemic had on the food supply chain. Lastly, we are interested in exploring the response of gold returns given contagious diseases because gold plays an important role as a traditional hedging instrument (Baur and McDermott, 2010 and Shahzad et al., 2020).

The whole theoretical idea of COVID-19 and asset markets comes from the fact that the COVID-19 outbreak can be considered to be a rare disaster risk whose effect on financial

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[1] The US benchmark stock market index

[2] The foreign exchange rate market made $6.6 trillion in the year 2019 from $5.1 trillion in 2016 as reported by the Triennial Survey of global foreign exchange market volumes of the Bank of International Settlement (BIS)

[3] In 2020, approximately 265 million people were affected by food insecurity, that is a 135 million increase due to the COVID-19 outbreak.

asset realised volatility is to be explored. Contemporary, there is a vast literature on the theoretical claim that extremely rare disaster risks are an important determinant of financial assets returns and volatility (see for instance, Gupta et al., 2019, Balicilar et al., 2022, Demirer et al., 2022, Salisu et al., 2022, Sheng et al., 2022 and Van Eyaden et al., 2022). This is because such shocks contain important information that can be transmitted into the financial market. From an economic viewpoint, given the relationship between the real economy and financial market through firms' cash flows and profitability expectations, it is arguable that the effect of rare disaster risks (Covid-19) on the financial market is partially driven by the unprecedented increased levels of uncertainty in economic activity (see a related study by Demirer et al., 2018). This has an adverse impact on macroeconomic factors such as aggregate production, consumption and investment.

In fact, the COVID-19 outbreak adversely affected our employment, finances, and mental and physical health apart from the lost lives[4] (Alonzi et al., 2020; Jackson et al.,2020). This resulted in high levels of uncertainties in the global economy. Unsurprisingly, this led to high financial market volatility (Zhang and Wei 2010; Kang et al. 2017). However, we lack related empirical studies on the forecastability of financial assets' realised volatility given infectious diseases-related uncertainty.

In the wake of contagious diseases, especially the COVID-19 outbreak, there was a tremendous interest in forecasting financial asset returns volatilities (Adediran et al., 2021, Bouri et al., 2021, Bouri et al., 2022, Caggiano et al., 2020, Gupta et al., 2021). This prompted questions of whether the US Treasury securities, international stocks, major foreign exchange rates, Bitcoin, agricultural commodities and gold futures can be considered by investors and portfolio managers for hedging benefits and portfolio diversification in times of infectious diseases-related uncertainty. Also, the interest of investors in the precise forecast of the volatility of these financial assets is in their assets' pricing derivatives and in designing hedging strategies when reducing their investments' risks.

Given limited studies on the predictability of financial assets amid contagious diseases, in particular the COVID-19 pandemic, the general objective of this Thesis is to uniquely

[4] Millions of workers faced sudden and unexpected joss loss while others had to adjust to the 'new normal' of working in isolation. This had a psychological strain of conducting work while distancing from others, wearing protective gear and constantly sanitizing.

investigate the predictive power of daily infectious diseases-related uncertainty on the realised volatility of financial assets.

Specific objectives:

- To investigate uncertainty related to infectious diseases and forecastability of the realised volatility of US Treasury securities (Chapter 2).
- Examine the predictability of the realised volatility of international stock markets amid uncertainty related to infectious diseases (Chapter 3).
- To study infectious diseases-related uncertainty and the predictability of foreign exchange and Bitcoin futures realised volatility (Chapter 4).
- To investigate the forecastability of agricultural commodity futures realised volatility with daily infectious disease-related uncertainty (Chapter 5).
- Lastly, we examine the relationship between contagious diseases and gold returns using over 700 years of evidence from quantile regressions (Chapter 6).

Several studies have been conducted on infectious disease and financial markets, especially since the incidence of the COVID-19 pandemic (see, for example, Salisu and Vo 2020; Salisu et al. 2020; Caggiano et al. 2020; Bouri et al. 2020b; Salisu and Sikiru 2020; Salisu and Adediran 2020; Salisu et al. 2020; Adediran et al. 2021; Liu et al. 2022). However, these studies focused mainly on stock returns. Using daily zero coupon yields of the US Treasury security on the dynamic conditional correlation (DCC) multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) model, Gupta et al. (2021) show that returns on US Treasury securities were adversely impacted by the COVID-19 outbreak. Lyócsa et al. (2020), point out that the fear of the COVID-19 pandemic is a valuable proxy for forecasting stock returns in the world as referenced by google search trends. Through the event study approach, Harjoto et al. (2020) study the reaction of the stock market to the Federal Reserve and WHO announcements in emerging and developed states using daily data. The results provide evidence that the COVID-19 pandemic had a negative shock on global stock markets with more shock on small firms and emerging markets. On the other hand, Ambros et al. (2020) do not find any sensitiveness of stock returns from COVID-19 new when using the Capital Asset Pricing Model (CAPM) and Ordinary Least Squares (OLS) model on Asia, US and Europe stock markets.

In 25 countries, Lyke (2020) looks at foreign exchange rate return and volatility prediction from 31 December 2019 to 08 May 2020 using the generalised Autoregressive conditional heteroskedasticity (GARCH) summary statistic, it is evident that diseases outbreak have better predictive power over exchange rate volatility. Mnif et al. (2020) present evidence that cryptocurrencies were more efficient as hedging instruments in the world from 31 December 2019 to 19 May 2020 when using the Media General Hurst Exponent.

Using time-varying parameter vector autoregression, Umar et al. (2020) assess the connectedness of dynamic return and volatility for commodity indexes (the softs) and coronavirus media coverage index from 01 January 2020 to 30 April 2021. The results indicate an overtime fluctuation of dynamic total returns and volatility connectedness with a peak observed in both the first and second waves. Kinateder et al, (2021) confirmed the safe haven nature of gold given infectious diseases-related uncertainty using the dynamic conditional correlation (DCC) GARCH model.

Some studies exist on commodity returns and infectious diseases. For example, using the nonparametric Granger causality-in-quantiles test, Balcilar et al. (2022), assessed the effect of COVID-19 (measured by the news-based sentiment index) on 13 major agricultural commodity prices and price volatility. They employed daily data over 73 months, i.e., from 1 January 2016 to 25 February 2022. Their findings suggest that in both the lower and upper quantile ranges, there is Granger causality from the pandemic to the average commodity prices. Furthermore, COVID-19 sentiment is causal to the price volatility of agricultural commodities in the quantiles above the first quarter.

Long and Guo (2022) analysed the effects of infectious disease equity market volatility and other factors on commodity returns. Results based on the time-varying Granger causality test and time-varying parameter vector autoregression with a stochastic volatility model showed that the time-varying effects are significant with mostly positive responses. They also found out that, of the five pandemics (Bird Flu in 1998, SARS in 2003, Swine Flu in 2009, MERS and Ebola in 2014, and COVID-19 in 2019) studied, the recent COVID-19 produced the greatest impact on commodity returns. Furthermore, they showed that the returns of five commodity subcategories, namely, textiles, industry, metals, livestock, and food, were most negatively impacted during the sample period, thereby making these commodities not safe haven assets during pandemic risks.

Akyildirim et al. (2022) used panel data regressions and time-varying Granger causality tests to examine whether the spillovers between agricultural commodity returns and sentiments are influenced by economic and financial uncertainties, including the global COVID-19 pandemic. They found that the agricultural commodity returns and sentiments were significantly influenced by COVID-19-induced uncertainty around the first cycle of the pandemic in 2020. Nascimento et al. (2022) used the Hurst exponent and multifractal detrended fluctuations analysis, and they found that, during the COVID-19 pandemic (from 1 January 2020 to 25 September 2020), sugar was the most efficient commodity, while pork was the least in the Brazilian agricultural commodity market. Daglis et al. (2020) analysed the impact of the COVID-19 pandemic on oats and wheat returns using data from 22 January 2020 to 2 June 2020. Results from the standard VAR model indicated that these markets were affected by COVID-19. Furthermore, these results indicated the out-of-sample forecasting superiority of a model that explicitly incorporates the COVID-19 pandemic over the baseline model.

Using data from 1 January 2020 and 30 April 2021, Umar et al. (2022) examined the dynamic return and volatility connectedness for three agricultural commodities indices (softs, grains, and livestock) and the coronavirus media coverage index (MCI). Results based on time-varying parameter vector autoregression showed that dynamic total return and volatility connectedness fluctuated over time, reaching a peak during both the first and the third waves of the COVID-19 pandemic. Cariappa et al. (2022) used time series data from 1 November 2019 to 10 August 2020 in conjunction with survey data to analyse the effect of COVID-19-induced lockdowns on agricultural commodity prices and consumer behaviour in India. Results from an interrupted time series analysis showed a significant rise in the prices of chickpeas (4.8%), mung bean (5.2%), and tomato (78.2%), although these reverted immediately after the lockdown. Furthermore, the Kruskal–Wallis test results showed a significant change in consumer behaviour through panic purchases.

Chen et al. (2022) used data from 2019 to 2021 and the Black (1976) model to show how the COVID-19 pandemic impacted the volatility of Chinese agricultural commodity options more strongly relative to non-agricultural commodities. Using causality in impulse response functions and variance tests and daily data from January 2020, Shruthi and Ramani (2021) found that the risk transmission among agricultural commodities was zero. According to Gutierrez et al. (2022), results from a global vector autoregression (GVAR) model revealed that the fall in the oil price may have contributed to the stability of the world grain market during the COVID-19 pandemic and that export restrictions could significantly increase global prices. An asymmetric analysis by Ayyildiz (2022) using the nonlinear autoregressive distributed lag model and data from 11 March 2020 to 11 March 2021 showed that the effect of an increase in the COVID-19 global fear index on agricultural commodity prices was greater than the effect of a decrease. According to the above, the majority of these studies focused on the COVID-19 pandemic while the current study uses an infectious disease uncertainty index that is broad and covers different infectious disease pandemics. Furthermore, all the studies except Daglis et al. (2020) conducted in-sample predictability analysis, while we conduct an out-of-sample analysis.

To accomplish the purpose of our Thesis we use daily intraday data computed within the 5-minutes interval in all our financial assets' realised volatility and then examine the predictive power of daily infectious diseases-related uncertainty by using the short-, medium- and long horizon recursive out-of-sample heterogeneous autoregressive realised variance (HAR-RV) model[5]. For our out-of-sample evaluation approach we employed McCracken (2007) MSE-F test[6]. In examining contagious diseases and gold returns we use annual data on real gold returns and the probability of fatality because of infectious diseases from 1258 to 2020. We detect nonlinearity and regime changes among the two variables of concern using the quantile regression model.

The remaining part of the Thesis is structured as follows. Chapter 2 presents uncertainty related to infectious diseases and forecastability of the realized volatility of US Treasury securities while Chapter 3 describes the predictability of the realised volatility of international stock markets amid uncertainty related to infectious diseases. Chapter 4 reports on infectious diseases-related uncertainty and the predictability of foreign exchange and Bitcoin futures realised volatility. Chapter 5 outlines the forecastability of agricultural commodity futures realised volatility with daily infectious disease-related uncertainty. Chapter 6 presents the relationship between contagious diseases and gold returns using over 700 years of evidence from quantile regressions. Then Chapter 7 concludes.

[5] This method addressed the problem of conditional heteroscedasticity usually encountered in higher frequency time series data like financial variables in this case. The issue of financial market returns volatility is best defined in quantitative term; and with the contribution of Baker et al. (2020) which quantified uncertainty related to infectious disease, there is no better approach to analyse the relationship financial market volatility and uncertainty related to infectious disease than quantitative research method.

[6] This MSE-F test provide asymptotic results for out-of-sample tests that compute the predictive power of two nested models when parameters are estimated allow for a wider range of loss functions not limited to square errors.

Chapter 2

Uncertainty Related to Infectious Diseases and Forecastability of the Realised Volatility of US Treasury Securities*

2.1. Introduction

Although the global financial market has become more integrated, the economic gains from holding a portfolio of Treasury securities of the United State (US) as traditional less risky "safe haven" are well-recognized (see Hartmann et al., 2004; Baur and Mcdermott, 2016; Kopyl and Lee, 2016; Gupta et al., 2021; Kinateder et al., 2021). Portfolio managers and investors are often attracted to this asset class because of its ability to offer portfolio diversification and hedging benefits during periods of negative market shocks, turmoil in traditional financial markets and economic uncertainty. The US Treasury securities are also considered as "safe-haven" by Kopyl and Lee (2016) because of their significant lack of default risk triggered by the fact that the US government has massive revenue streams that are approximately over 20% of the global output. Cheema and Szulczuk (2020) argue that the US Treasury security market remains one of the largest risk-free and most liquid financial markets in the global economy.

Unsurprisingly, an accurate forecast of the volatility of the US Treasury securities is of tremendous interest to portfolio managers and investors in the pricing of the US Treasury securities and in designing hedging strategies against portfolio risks exposure. These securities have also received high attention in academia, previous financial literature has attempted to predict the future path of the US Treasury securities based on various factors (for example see Hoti et al., 2009; Çepni et al., 2021, 2020). Recently, the COVID-19 outbreak has resulted in unprecedented levels of uncertainties over our economy, employment[7], finances and of course over our mental and physical health (Alonzi et al., 2020; Jackson et al., 2020). However, we lack empirical evidence on the predictive power of the daily infectious diseases-related uncertainty for the US Treasury securities' realised volatility (RV)[8]. As highlighted recently

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[7] In March 2020, the US experienced a job loss of approximately 3.28 million, which is the highest record ever.

[8] When thinking about volatility, we need to consider the risks and opportunities or rewards aspects. More often than not, we think of volatility in term of assets allocation, assets pricing and risks management and overlook its opportunities aspect that may generate returns. However, we need volatility to generate returns. Volatility can also be considered in terms of the market environment. That is, what it tells us about the market environment and how much uncertainty is there in the market we are looking at.

through a related study by Gupta et al. (2021), yields of US Treasuries bonds tend to be negatively impacted by the uncertainty associated with the outbreak of COVID-19, i.e., the associated increase in the US Treasury securities' returns is likely to enhance volatility due to higher trading.

Given the above, the objective of this chapter is to examine for the first time the predictive power of the daily newspaper-based index uncertainty related to infectious diseases (EMVID) of various types (such as MERS, SARS, Ebola, H5N1, H1N1 and most importantly the Coronavirus) for the following US Treasury securities; the US 2-Year Treasury-Note (T-Note), the US 5-Year T-Note and the US 10-Year T-Note futures as well as the US 30-Year Treasury-Bond (T-Bond) futures RV over the short-, medium- and the long forecast horizon (h = 1, h = 5 and h = 22). As further analysis, we also examine the predictability of the EMVID index for the Canadian 10-Year T-Notes futures and the Eurodollar[9] futures CME RV. In quantifying the economic uncertainty associated with infectious diseases, we use the newspaper-based index of Baker et al. (2020). The index tracks daily equity-market volatility (EMV), especially in the Chicago Board Options Exchange (CBOE) and the Volatility Index (VIX). This index is advantageous as it satisfies more time-series data features, has a time lag, is forward-looking, and it fits for real-time COVID-19 analysis. Most importantly, its frequency is daily, thus, intraday data contains accurate and depth information that may lead to more precise estimates and forecasts for daily volatility as advocated by Bonato et al. (2021).

Taking into account the latter, we contribute to the research on the US Treasury securities by forecasting their RV computed from 5-minute-interval intraday data, we adopt the modified version of the heterogeneous autoregressive (HAR) model introduced by Corsi (2009). In particular, we extend the benchmark heterogeneous autoregressive realised variance (HAR-RV) model by adding the EMVID index and examine its ability to predict the future path of the US Treasury securities from 2nd September 2011 to 20th February 2021. This data period covers various market phases of our economy and the recent COVID-19 pandemic that led to tremendous global economic uncertainties.

According to Flavin et al. (2014), longer-dated bonds are traditional "safe haven" assets because they have the ability to offer fund managers and investors portfolio diversification and hedging benefits during periods of economic downturns. Also, a related study by Gupta et al. (2021) analyse the role of the US Treasury bonds as safe-haven assets given financial markets

[9] The Eurodollar is the term that refers to any US dollar held outside the United States banking system.

uncertainty from contagious diseases. Using the dynamic conditional correlation-multivariate generalised autoregressive conditional heteroskedasticity (DCC-MGARCH) framework they provide evidence that the EMVID index play a significant role in predicting the future path of the US Treasury bonds. Also, these assets can be used as hedging instruments against the Covid-19 pandemic. Therefore, we expect our results to show that the daily newspaper-based index uncertainty related to infectious diseases plays a role in explaining the US Treasury securities in the long run.

The rest of our chapter is organized as follows. Section 2.2 presents the data and methodology; Sec. 2.3 depicts the results; Sec. 2.4 presents the conclusion.

2.2. Data and Methodology

2.2.1. Data

Data on the US Treasury securities' RV is directly sourced at the University of Chicago Booth School of Business Risk Lab where it is maintained by Professor Dacheng Xiu. This data can be publicly accessed at https://dachxiu.chicagobooth.edu/#risklab. Trades are collected up to the highest frequency available and cleaned using the prevalent national best bid and offer (NBBO) that is available every second. The RV estimation procedure follows (Xiu, 2010) and is determined using quasi-maximum likelihood estimation of volatility (QMLE) based on moving average models MA(q), using non-zero returns of transaction prices sampled up to its available frequency for days with at least 12 observations. The Akaike Information Criterion (AIC) is employed in choosing the best MA(q). For our analysis, we used the 5-minute RV estimates.

Data on daily infectious diseases-related uncertainty (EMVID) is developed by Baker et al. (2020). They contract it using a newspaper-based infectious disease equity market volatility tracker from January 1985. This data is publicly available for download from http://policyuncertainty.com/infectious_EMV.html. In constructing the EMVID, the authors specify four terms, 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, Imola, H5N1 and H1N1. Second, daily counts of newspaper articles that contain at least one term in each of E.M.V and ID across approximately 3000 US newspapers. Furthermore, the raw EMVID counts are scaled by the counts of all articles on the same day. Multiplicatively, Baker et al. (2020) rescale the resulting series to match the level of the VIX through the overall EMV index and scale the EMVID index articles to total EMV articles. Our data in both series range from 2nd September 2011 to 20th February 2021. This is based on data availability and the earliest possible date from our estimation. The data range covers the tremendous economic uncertainty due to COVID-19 and other markets event such as the global financial crisis. The descriptive statistics and plots are presented in the appendix, Table A2.1 and Fig. A2.1, respectively.

2.2.2. Methodology: Heterogeneous Autoregressive Realised Variance Model

In achieving the purpose of this chapter, we employ the HAR-RV model of Corsi (2009) for the out-of-sample predictability analysis. As an additive cascade model of different volatility components realised in different time horizons, the HAR-RV model can reproduce the main empirical features observed in financial data, long memory, fat tails and self-similarity, while remaining parsimonious and easy to regress (Gkillas et al., 2020). The benchmark HAR-RV model.

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \varepsilon_{t+h} \tag{1}$$

The h index represents h-days ahead RV, where h = 1, 5 and 22. $RV_{w,\,t}$ and $RV_{m,\,t}$, denotes the average RV from day t-6 to day t-1 and day t-22 to day t-6, respectively. Adding the EMVID index to the benchmark HAR-RV model yield the extended HAR-RV model:

$$RV_{t+i} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta EMVID_t + \varepsilon_{t+i} \tag{2}$$

2.3. Empirical Results

The primary objective of this chapter is to examine the ability of the EMVID index in predicting the future path of the US Treasury securities' RV (the US 2-, 5- and 10-Year T-Note and the US 30-Year T-Bond futures) from 2nd September 2011 to 20th February 2021. For analysis purposes, we incorporate the Canadian 10-Year T-Note and the Eurodollar futures CME RV. As advocated by Bouri et al. (2020), the definitive test for any predictive model is in its out-of-sample performance. We study the out-of-sample predictability of our International Bonds by considering a recursive estimation approach over the period under investigation. Firstly, we start by diagnosing the breakpoints of the HAR-RV model using the multiple structural break test by Bai and Perron (2003). The following breaks were determined; 2nd July 2013, 9th May 2013, 11th June 2013 and 28th June 2012 for the US 5-,2-, and 10-Year T-Notes and the US 30-

Year T-Bond futures, respectively. These are our earliest breakpoints across the three forecasting horizons. These multiple breakpoints from 2012 - 2013 can be attributed to the civil war in Syrian and the conflicts in the Middle East crisis (Broadstock and Filis, 2014). These triggered positive oil-market specific shocks (price hikes) and the markets responded negatively. Our recursive estimation starts from these points onward, we then compare the root mean squared forecast errors (RMSFEs) for the benchmark HAR-RV model and the extended HAR-RV model that include the EMVID index under h =1, h = 5 and h = 22. For forecasting accuracy between the benchmark and extended HAR-RV model, we conduct the MSE-F test[10] of McCracken (2007).

Next, we present the out-of-sample RMSFEs for both the benchmark and extended HAR-RV models in Table 2.1 Most importantly, our main focus is on forecasting, therefore, lower values of the RMSFEs in the latter models indicate a better-performing model. The out-of-sample forecasting gains are computed using the following formula:

$$FG = \left(\frac{RMSFE_0}{RMSFE_1} - 1\right) * 100 \tag{3}$$

where $RMSFE_0$ and $RMSFE_1$ are the RMSFEs of the benchmark and extended HAR-RV models, respectively. In general, positive or negative FGs indicate a gain or loss in percentages, respectively. In terms of the RMSFEs metrics related to the forecasting accuracy of the US Treasury securities, our out-of-sample results (Table 2.1) indicate that considering the information contained in the daily newspaper- based index uncertainty related to infectious diseases, an econometrician can acquire 3.32% and 0.04% forecasting gains in the US 5-Year T-Note futures in the h =1 and h = 5 respective time horizons. In the US 10-Year T-Note, an econometrician can acquire 0.02% and 0.10% forecasting gains in the h = 1 and h = 22-time horizons, respectively. It is evident that across all the time horizons in the US 30-Year T-Bond futures, an econometrician can acquire 0.24%, 0.016% and 0.17% forecasting again[11] (h = 1, h = 5 and h = 22, respectively) while becoming indifferent in the forecasting gain/ loss of the US 2-Year T-Note futures[12].

According to the MSE-F statistics, the results of the US 30-Year T-Bond (MSE-F statistics: 8.9517, 5.7317 and 6.26 for h = 1, h = 5 and h = 22, respectively)

[10] MSE-F = (T-R-h+1)dhat/MSE1

[11] An econometrician can acquire statistically significant forecasting gains (1.90, 1.18 and 4.06 in the h = 1, h = 5 and h = 22 horizons, respectively) from the Eurodollar futures.

[12] This indifference in forecasting gain/loss in the Canadian 10-Year T-Note futures in evidence.

Table 2.1. Out-of-Sample Forecasting Gains

Horizon	$RMSFE_0$	$RMSFE_1$	FGs
Panel A: CGB – 12th April 2000 to 20th February 2021			
h=1	0.0156	0.0156	0.0000
h=5	0.0041	0.0041	0.0000
h=22	0.0010	0.0010	0.0000
Panel B: ED - 06th July 2016 to 20th February 2021			
h=1	0.2803	0.2751	1.9008***
h=5	0.0748	0.0739	1.1812***
h=22	0.1407	0.1352	4.0592***
Panel C: FV - 02nd July 2013 to 20th February 2021			
h=1	0.0094	0.0091	3.3223***
h=5	0.0024	0.0024	0.0422***
h=22	0.0006	0.0006	0.0000
Panel D: TU - 09th May 2013 to 20th February 2021			
h=1	0.0036	0.0036	0.0000
h=5	0.0010	0.0010	0.0000
h=22	0.0002	0.0002	0.0000
Panel E: TY - 11th June 2013 to 20th February 2021			
h=1	0.0140	0.0140	0.0214***
h=5	0.0037	0.0037	0.0000
h=22	0.0010	0.0010	0.1012***
Panel F: US - 28th June 2013 to 20th February 2021			
h=1	0.0243	0.0243	0.2431***
h=5	0.0064	0.0064	0.1561***
h=22	0.0017	0.0017	0.1720***

Notes: CGB: Canadian 10 Year Futures, ED: Eurodollar Futures CME, FV: US 5-Year T-Note Futures, TU: US 2-Year T-Note Futures, TY: US 10-Year T-Note Futures and US: US 30-Year T-Bond Futures. The out-of-sample forecasting gain is computed as follows $FG = \left(\frac{RMSFE_0}{RMSFE_1} - 1\right) * 100$, where $RMSFE_0$ and $RMSFE_1$ are root mean squared forecast errors (RMSFEs) of the benchmark (eq 1) and extended HAV-RV model (eg. 2), respectively. The entire sample was used as the in-sample range. Where *** indicates 1%. level of significance.

are statistically significant at all levels of significance while the results of the US 5- Year T-Note are only significant at the h = 1 and h = 5-time horizons with MSE-F statistics of 123.4133 and 1.5387, respectively. The results of the US 10-Year T-Note are statistically significant at the h = 1 and h = 22 horizons with MSE-F statistic values of 0.7944 and 3.7104, respectively. In contrast, the results of the US 2-Year T-Note futures are insignificant at all levels. The MSE-F critical[13] values are obtained from Table 4 of McCracken (2007). These results indicate that

[13] MSE-F Critical values are 3.951, 1.518 and 0.616 at 10%, 5% and 1% level of significance, respectively.

daily infectious diseases-related uncertainty has or rather contains important information for forecasting the clear path of the US Treasury securities.

To cover for the COVID-19 episode, we conduct our analysis where the in-sample estimation is till the end of December 2019 and the out-of-sample forecast starts from the first date of January 2020 till the end date of our data. In our case, the breaking point is on 3rd January 2021. Most importantly, this is the time when the entire globe started to experiencing the pandemic and panic reactions from economic agents propelled the impact of the virus on our economies (Gopinath, 2020). This was pure because COVID-19 was and still a death threat. Our results show that an econometrician according to the metrics of the RMSFEs can acquire 0.17%, 0.26% and 0.16% forecasting gain in the three respective forecasting models, etc., h = 1, h = 5 and h = 22 in the US 5-Year T-Note. In the US 2-Year T-Note, an econometrician can acquire 0.03, 0.12 and 0.38 forecasting gains in the h = 1, h = 5 and h = 22, respectively. Another forecasting gain of 0.74%, 0.47% and 0.16% (in the h = 1, h = 5 and h = 22 model, respectively) that an econometrician can inference from is evident in the US 30-Year T-Bond futures. On the other hand, an econometrician can obtain a forecasting loss of -0:01% and – 0.03% in the h = 1 and h = 5 forecasting models of the US 10-Year T-Note. Our results emphases that the role of government securities, in particular, the US Treasury securities in national and international markets is crucial amid contagious diseases. That is, they still serve as a benchmark interest rate, hedging interest rate risk, position funding and liquidity management, investment and position taking and government securities as near-monies and safe-haven (Schinasi et al., 2001).

According to the MSE-F statistics[14], the results of our out-of-sample models in the COVID-19 range for the US 5- and 2-Year T-Notes and the US 30-Year T-Bond are statistically significant at a 1% level of significance. The results of our out-of-sample models in the US 10-Year T-Note are statistically insignificant[15] at all levels of significance[16]. It is worth notable that even in such a short period we can empirically see the predictive power of the EMVID for especially the US 5- and 2-Year T-Notes (the US 2-Year T-Note was previously insignificant) and the US 30-Year T-Bond. This has important implications for investors during periods of turmoil uncertainties due to epidemics and pandemic outbreaks.

[14] The MSE-F statistic values are available on request. They are to be compared with the MSE-F critical values of 1.608, 0.85 and 0.53 at 10%, 5% and 1% level of significance, respectively.
[15] The MSE-F critical value is less than the MSE-F statistics.
[16] The US 10-Year T-Notes are long forecast while the COVID-19 range was short at the time of our estimation.

Our findings contribute to the existing literature by showing that uncertainty related to pandemics and epidemics has the ability to predict the volatility of the US Treasury securities. This is the first unique empirical evidence from previous literature related to the predictive power of uncertainties of various types (economic, financial, as well as geopolitical risk) for this asset class.

2.4. Conclusion

The role of the US Treasury securities as a premier "safe haven" during periods of uncertainty is well recognized in the financial market as well as in academia. The unprecedented levels of global uncertainty as a result of the COVID-19 outbreak have caused us to uniquely examine the predictive ability of the daily newspaper-based index uncertainty related to infectious diseases (EMVID) for the US Treasury securities' RV. Extending the benchmark heterogonous autoregressive volatility (HAV-RV) model by adding the EMVID index, our out-of-sample forecast shows significant evidence of the role played by the EMVID index in explaining the future path of the US Treasury securities.

To evaluate the predictive power of the EMVID index in-depth, we conducted the out-of-sample forecast over the period that covers the COVID-19 episode. Our results depict that over this short period, the role of the EMVID index in forecasting the US Treasury securities under investigation is statistically significant except in the US 10-Year T-Note futures. These findings have important implications for fund managers and investors during times of economic downturns.

Incorporating daily infectious diseases-related uncertainty in the forecasting model can help improve the structuring of the portfolio that includes the US 30-Year T-Bond and the US 2-and 5-Year T-Notes futures as a hedging instrument in the financial market during periods of infectious diseases outbreak. Hence, the accurate forecast of this asset class is important. For future studies, it would be interesting to study how infectious diseases related uncertainty have affected other financial sectors such as the international stock markets, foreign exchange markets, cryptocurrency markets as well as the commodity markets.

Chapter 3

Predictability of the Realised Volatility of International Stock Markets Amid Uncertainty Related to Infectious Diseases[ξ]

3.1. Introduction

The coronavirus pandemic has questioned the traditional "safe haven" nature of the international stock markets index (Kopyl and Lee, 2016; Gupta et al., 2021; Kinateder et al., 2021; Kizys et al., 2021), casting doubts on whether these markets can be considered attractive for portfolio diversification and hedging benefits in periods of infectious disease.

In fact, the COVID-19 outbreak was followed by remarkable negative responses in stock market returns, as reported in recent academic literature (Al-Awadhi et al., 2020; Harjoto et al.,2021; Lyócsa et al., 2020; Zhang et al., 2021; Gao et al., 2021; Mazur et al., 2021; Ashraf, 2021). In that time period, the US benchmark stock markets index, the S&P 500 declined by approximately 4.9%, the Nasdaq decreased by 4.7% and the Dow Jones experienced its biggest drop since 1987 (Wang et al., 2020). Furthermore, Lyócsa et al. (2020), for example, showed that the fear of the coronavirus (measured as the google search volume on this topic) is a valuable variable to predict stock price changes around the world. Moreover, Lyócsa and Molnár (2020), Zaremba et al. (2020), Zhang et al. (2020), Gao et al. (2021) and Mazur et al. (2021) allude that all crises, including the COVID-19 pandemic, have one common feature, i.e., extreme market volatility (Zhang and Wei, 2010; Kang et al., 2017). Stock market volatility has been a topic of interest in the academic literature, since stock market volatility is a key feature for option pricing, financial market regulation, investment or hedging decisions (Poon and Granger, 2003; Chen et al., 2019; Shiba and Gupta, 2021), so that many papers attempt to predict stock market volatility. In the framework of this literature, this chapter analyses to what extent the uncertainty related to infectious diseases play a significant role in forecasting the volatility of a sample of thirty-one international stock markets.

Furthermore, according to the academic literature, global crises trigger an increase in the connectedness among stock markets. However, the reaction of different stock markets to the crisis was not uniform across countries (Ashraf, 2021). In this context, Zhang et al. (2021),

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for example, find volatility spillovers from China to other advanced economies during COVID-19, while they do not find volatility spillovers from those countries to China. On the other hand, the COVID-19 risk spillovers from stock markets in American and European regions increased rapidly but they were minimal for the stock markets in Asia (Liu et al., 2021). Interestingly, Khan et al. (2020) argue that the volatility of the Shanghai Composite Index was minimal due to the drastic and firm measures taken by the Chinese government to contain the spread of the virus, which boosted investor confidence. Zaremba et al. (2021) also find that rapid government policy responses tend to support international stock markets during the pandemic. Furthermore, the government's intervention by restricting commercial activities, introducing the wearing of masks and enforcing social distancing, played a crucial role in containing the spread of COVID-19, and gaining stability again in the market (Baker et al. 2020b). Despite the recent literature on the impact of COVID-19 on financial markets, there is a lack of empirical evidence on the forecasting power of the daily infectious diseases-related uncertainty for international stock market volatility.

In this framework, the objective of this chapter is to analyse the predictability of daily infectious diseases-related uncertainty (EMVID) for international stock market volatilities using the heterogeneous autoregressive realised variance (HAR-RV) model. The key feature of the HAR-RV model is that it uses volatilities from different time resolutions to forecast the realised volatility of equity returns. The model, thereby, captures the main idea motivating the heterogeneous market hypothesis (Müller et al., 1997). This hypothesis stipulates that different classes of market participants populate the stock market, where traders in the different classes differ in their sensitivity to information flows at different time horizons (that is, short-term traders versus long-term traders). For example, traders and speculators are very sensitive to short-term investment horizons, whereas investors are more concerned with long-term investment horizons.

The main contributions of this chapter are the following. First, we investigate the ability of uncertainty related to infectious diseases using daily data from January 2000 to June 2021, that is, the analysis includes not only the recent COVID-19 outbreak, but it also includes other infectious diseases such as the H1N1 pandemic in 2009–2010, the Ebola outbreak in 2014–2016, the H5N1, MERS or SARS viruses, etc. As a measure of infectious diseases-related uncertainty, we use the newspaper-based index by Baker et al. (2020a). This index tracks the daily equity-market volatility (EMV) in the Chicago Board Options Exchange (CBOE) volatility index. This measure is suitable for a statistical model for predicting the volatility of the international stock markets index. We employ intraday data as it contains information that may lead to more precise and accurate estimates and forecasts. Second, our chapter contributes to the literature of the international stock markets index by forecasting its realised volatility computed from 5 min-intervals using the modified version of the heteroscedasticity autoregression (HAR-RV) model by Corsi (2009). More precisely, we extend the benchmark HAR-RV model by adding the daily EMV due to infectious diseases (EMVID) and assess its ability to forecast the international stock markets index RV. Third, we consider out-of-sample short- (h = 1), medium- (h = 5) and long forecast horizon of the (h = 22) predictability of EMVID for international stock market volatility. Finally, the chapter studies the predictability of EMVID on the volatilities of 31 international stock market indexes, allowing for international differences in the responses of stock markets to each of the EMVID episodes. This analysis will shed some light on the international portfolio diversification possibilities.

The remainder of the chapter is organized as follows. Section 3.2 presents the data and describes the methodology. Section 3.3 outlines the empirical results, Section 3.4 includes a discussion of the main results and Section 3.5 concludes.

3.2. Data and Methodology

3.2.1. Data

The data on the international stock market RV are sourced directly from the Oxford-Man Institute of Quantitative Finance. We use the Oxford-Man all stock markets index, which is publicly available at: https://realized.oxford-man.ox.ac.uk/data (accessed date: 1 June 2021) These data contain daily close-to-close non-parametric financial returns $(r_{1,} r_2 \ldots\ r_T\ )$ on international indexes together with their corresponding realised $(RM_{1,} RM_2 \ldots\ RM_T\ )$ which are the realised variances. $RM_t = \sum x_{j,t}^2$, where $x_{j,t}\ =\ X_{t_{j,t}}\ - X_{t_{j-1,t}}$. $t_{j,t}$ is the time of trade on the t-th day. If the prices are without noise, then as $min_j |t_{j,t}\ - t_{j-1,t}| \downarrow 0$, it consistently estimates the quadratic variation of the price process on the t-th day.

Data on the daily infectious diseases-related uncertainty (EMVID) index are developed by Baker et al. (2020a) using a newspaper-based infectious disease equity market volatility tracker from January 1985. The EMVID index is publicly accessible at: http://policyuncertainty.com/infectious_EMV.html (accessed date: 6 June 2021). This index is based on textual analysis of four sets of 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, Imola, H5N1 and H1N1. In approximately 3000 US newspaper articles, a daily count of at least one term in each of the EMV and ID is attributed in the EMVI index. Contemporary, the counts of all articles on raw EMVID are scaled on the same day. Lately, Baker et al. (2020a) multiplicatively rescale the final series to match the level of the VIX through the overall EMV index and the EMVID index is scaled to total the EMV articles. The range of our data varies according to the earliest data available to the latest possible date from our regressions. Interestingly, our data range covers the disastrous COVID-19 virus and other market events such as the global financial crisis. Note that the EMVID index is the only available measure of uncertainty due to various infectious diseases, including that of the coronavirus. Appendix A, Tables A3.1, Figure A3.1 and Table A3.2, present the acronyms of each stock market, the time series plots, and the out-of-sample results of the COVID-19 episode, respectively.

The data plots in Figure A3.1 depict a constant long-run trend across all the international stock markets index and EMVID during the pre-COVID-19 period, though there are some spikes that quickly return to the mean in the RV series. During the COVID-19 pandemic, we observe a high level of volatility in all the stock market indexes.

3.2.2. Methodology: Heterogeneous Autoregressive Realised Variance (HAR-RV) Model

To accomplish the primary purpose of this chapter, the out-of-sample predictability analysis is conducted using the HAR-RV model by Corsi (2009). In its simplest structure, this model can reproduce important properties contained in financial data, such as long memory, fat tails, self-similarity and multi-scaling behaviour in a satisfactory way (Wang et al., 2019). The benchmark HAR-RV model is

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \varepsilon_{t+h} \tag{1}$$

where h is an index that represents the RV h-days ahead. In our case, h = 1, 5 and 22. $RV_{w.t}$ depicts the mean RV from day t - 6 to day t - 1, while RVm.t represents the average RV from day t - 22 to day t - 6. To capture the interest of our study, we add the EMVID index to the above benchmark HAR-RV model (Equation (1)), obtaining the following extended HAR-RV model:

$$RV_{t+i} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta EMVID_t + \varepsilon_{t+i} \tag{2}$$

3.3. Empirical Results

In terms of econometric modelling and predictability, Campbell (2008) and Bouri et al. (2020) argue that an ultimate test for any predictive model is related to its out-of-sample performance. In this chapter, our focus is on the out-of-sample predictability of the international stock markets index RV, i.e., we analyse the role of EMVID in forecasting the RV of the international stock markets index. We consider a recursive estimation approach over the out-of-sample period from the earliest data available in each index to the latest date from our estimation. To obtain the out-of-sample multiple structural break test used in the HAR-RV model, we perform the Bai and Perron (2003) test of 1 to M globally determined breaks and obtain the break dates using the UD_{Max} and WD_{Max} statistics, and the results are presented in Table 3.1.

Table 3.1. Structural Breakpoints.

	Continent				
Structural Breakpoints	**Europe**	**Asia**	**North America**	**South America**	**Australia**
2002		STI			
2003	AEX, BFX, FCHI, GDAX1, IBEX and STOXX50E	N225 and SSEC	DJI, IXIC, MXX, RUT and SPX		AORD
2004	FTSE and SSMI		BSESN, HIS, KS11 and NSEI	BVSP	
2005	OSEAX	KSE	GSPTSE		
2007	SMSI				
2008	OMXC20, OMXHPI and OMXSPI				
2011	FTMIB				
2014	BVLG				

Note: AEX: Amsterdam Exchange index, BFX: Bell 20 Index, BVLG: Portugal Stock Index (PSI) All-Share Index, FCHI: Cotation Assistée en Continu (CAC) 40, FTMIB: Financial Times Stock Exchange (FTSE), Milano Indice di Borsa (MIB), FTSE: FTSE 100, GDAXI: Deutscher Aktienindex (DAX), IBEX: IBEX 35 Index, OMXC20: OMX Copenhagen 20 Index, OMXHPI: OMX Helsinki All Share Index, OMXSPI: OMX Stockholm All Share Index, OSEAX: Oslo Exchange All-share Index, SMSI: Madrid General Index, SSMI: Swiss Stock Market Index, STOXX50E: EURO STOXX 50 , BSESN: S&P BSE Sensex, HIS: HANG SENG Index, KS11: Korea Composite Stock Price Index (KOSPI), KSE: Karachi SE 100 Index, N225: Nikkei 225, NSEI: NIFTY 50, SSEC: Shanghai Composite Index, STI: Straits Times Index, DJI: Dow Jones Industrial Average, GSPTSE: S&P/TSX Composite index, IXIC: Nasdaq 100, MXX: IPC Mexico, RUT: Russel 2000, SPX: S&P 500 Index, BVSP: BVSP BOVESPA Index, and AORD: All Ordinaries. The structural breakpoints are indicated in each index in their respective continent.

As reported in Table 3.1, most of the international stock market indexes experienced a structural break in 2003. In fact, market indexes in Europe (AEX, BFX, CHI, GDAX1, IBEX and STOXX59E), Asia (N225 and SSEC) North America (DJI, XIC, MXX, RUT and SPX) and Australia (AROD) were hit by a break in 2003. Several stock market indexes in Europe (FTSE and SSMI), North America (BSESN, HIS, KS11 and NSE) and South America (BVSP) suffered a break in 2004. In 2005, the structural breakpoints are evident in the European OSEAX, Asian KSE and North American GSPTSE market indexes. It is worth mentioning that structural breaks in 2007, 2008, 2011 and 2014 were only found in stock market indexes in Europe (SMSI, OMXC20, OMXHPI, OMXSPI, FTMIB and BVLG). On the contrary, the Asian STI market index suffered a structural break in 2002. The energy crisis in the early 2000s and the global financial crisis may explain the 2003 as well as the 2008 structural breaks in these indexes (Boubaker et al., 2020). The depreciation of the US dollar (Headey 2011) in 2011 explains the 2011 structural break whereas the 2014 breakpoint can be explained by the Ebola outbreak in 2014.

Given these breakpoints, and as we compute the root mean squared forecast errors (RMSFEs) for both the benchmark and extended HAR-RV model for h = 1, 5 and 22, our recursive estimation starts from the earliest date observed breakpoint for each of the indexes. To compute the forecast accuracy for the two latter models, the MSE-F test[17] by McCracken (2007) is employed. Table 3.2 presents the out-of-sample RMSFEs for the benchmark and the extended HAR-RV models. Since our primary purpose is to forecast, lower values of the RMSFEs in the out-of-sample models will indicate a better-performing model. In order to compute the out-of-sample forecasting gains (FG), the following formula is used:

$$FG \ = \ \left(\frac{RMSFE_0}{RMSFE_1} - 1\right) * 100 \tag{3}$$

Given Equation (3), positive or negative values of FG indicate the gains or losses in percentage. Out-of-sample results (Table 3.2) indicate that the STI (Singapore) has the highest FG of 0.36% in the h = 1 day horizon followed by an FG of 0.31% in the h = 1 day horizon for BVLG (Portugal), then an FG of 0.27% in h = 5 for STI and AORD, Australia (h = 1 and 5). This implies that considering the information context of the daily newspaper-based index

[17] MSE-F = (T-R-h+1).dhat/MSE1

uncertainty related to infectious diseases in terms of the forecast accuracy of the RMSFEs metrics, the highest FG of 0.36% is obtained in h = 1 for STI, with the second-highest FG of 0.31% on the h = 1-day horizon for BVLG, then an FG of 0.27% for STI (h = 5) and AORD (h = 1 and 5).

Table 3.2. Out-of-Sample Forecasting Gains.

Horizon	$RMSFE_0$	$RMSFE_1$	FGs	$RMSFE_0$	$RMSFE_1$	FGs
Europe						
	Panel 1: AEX. 8/05/2003			Panel 2: BFX. 7/04/2003		
h=1	1.3045	1.3038	0.0571 ***	1.1004	1.0985	0.1751 ***
h=5	0.3400	0.3398	0.0412	0.2957	0.2955	0.0805 ***
h=22	0.0886	0.0886	0.0406	0.0741	0.0741	0.0108
	Panel 3: BVLG. 5/23/2014			Panel 4: FCHI. 8/05/2003		
h=1	0.5028	0.5012	0.3110 ***	1.5860	1.5852	0.0510 ***
h=5	0.1272	0.1270	0.1456 ***	0.4106	0.4105	0.0244
h=22	0.0363	0.0363	0.1020	0.1049	0.1049	0.0124
	Panel 5: FTMIB. 9/07/2011			Panel 6: FTSE. 6/16/2004		
h=1	1.0066	1.0061	0.0562	2.3748	2.3740	0.0337
h=5	0.2611	0.2611	0.0069	0.6379	0.6376	0.0453 ***
h=22	1.5762	1.5746	0.1050 ***	0.1544	0.1544	0.0071
	Panel 7: GDAX1. 11/27/2003			Panel 8: IBEX. 5/14/2003		
h=1	1.6491	1.6488	0.0169	1.6762	1.6756	0.0367
h=5	0.4298	0.4297	0.0014	0.4403	0.4403	0.0191
h=22	0.1123	0.1122	0.0134	0.1129	0.1128	0.0346
	Panel 9: OMXC20. 10/15/2008			Panel 10: OMXHPI. 10/17/2008		
h=1	2.9683	2.9674	0.0291	4.2473	4.2464	0.0214
h=5	0.8047	0.8046	0.0211	1.1248	1.1246	0.0179
h=22	0.2017	0.2016	0.0198	0.2787	0.2787	0.0165
	Panel 11: OMXSPI. 10/02/2008			Panel 12: OSEAX. 10/06/2005		
h=1	2.5614	2.5610	0.0158	3.7652	3.7651	0.0007
h=5	0.5640	0.5640	0.0080	0.9853	0.9853	0.0036
h=22	0.1646	0.1646	0.0158	0.2398	0.2398	0.0142
	Panel 13: SMSI. 12/17/2007			Panel 14: SSMI. 3/29/2004		
h=1	2.1409	2.1398	0.0491	1.4816	1.4812	0.0238
h=5	0.5566	0.5564	0.0259	0.3832	0.3830	0.0368
h=22	0.1392	0.1391	0.0374	0.0988	0.0988	0.0051
	Panel 15: STOXX50E. 8/07/2003					
h=1	2.4806	2.4795	0.0454 ***			
h=5	0.6680	0.6677	0.0368			
h=22	0.1606	0.1606	0.0062			
Asia						
	Panel 16: BSESN. 6/16/2004			Panel 17: HIS. 11/09/2004		
h=1	2.8070	2.8047	0.0822 ***	1.2294	1.2294	0.0009
h=5	0.7339	0.7334	0.0608 ***	0.3281	0.3281	0.0003
h=22	0.2083	0.2082	0.0404	0.0793	0.0793	0.0025
	Panel 18: KS11. 6/16/2004			Panel 19: KSE. 4/01/2005		
h=1	1.2386	1.2384	0.0161	1.2807	1.2801	0.0478 ***
h=5	0.3273	0.3273	0.0095	0.3395	0.3393	0.0601 ***

h=22	0.0860	0.0860	0.0058	0.0840	0.0840	0.0012
	Panel 20: N225. 6/06/2003			Panel 21: NSEI. 5/18/2004		
h=1	1.3336	1.3332	0.0304	3.5197	3.5167	0.0865 ***
h=5	0.3479	0.3479	0.0089	0.9980	0.9974	0.0552
h=22	0.0897	0.0897	0.0111	0.2498	0.2497	0.0401
	Panel 22: SSEC. 11/18/2003			Panel 23: STI. 2/28/2002		
h=1	1.9674	1.9673	0.0066	0.3886	0.3872	0.3634 ***
h=5	0.5201	0.5200	0.0060	0.1032	0.1029	0.2681 ***
h=22	0.1350	0.1350	0.0000	0.0253	0.0253	0.0830 ***
North America						
	Panel 24: DJI. 5/23/2003			Panel 25: GSPTSE. 11/25/2005		
h=1	2.0634	2.0629	0.0220	4.9173	4.9166	0.0131
h=5	0.5358	0.5357	0.0088	1.2551	1.2550	0.0053
h=22	0.1372	0.1372	0.0146	0.3107	0.3107	0.0077
	Panel 26: IXIC. 4/30/2003			Panel 27: MXX. 4/30/2003		
h=1	1.3706	1.3699	0.0496 ***	1.4505	1.4502	0.0177
h=5	0.3524	0.3523	0.0304	0.3870	0.3870	0.0116
h=22	0.0601	0.0601	0.0000	0.0930	0.0930	0.0075
	Panel 28: RUT. 4/29/2003			Panel 29: SPX. 4/25/2003		
h=1	1.2246	1.2232	0.1099 ***	1.8266	1.8264	0.0097
h=5	0.3199	0.3196	0.0798 ***	0.4807	0.4807	0.0046
h=22	0.0833	0.0833	0.0012	0.1217	0.1217	0.0132
	South America			Australia		
	Panel 30: BVSP. 10/21/2004			Panel 31: AORD. 5/02/2003		
h=1	1.8477	1.8470	0.0405	1.0930	1.0900	0.2710 ***
h=5	0.4764	0.4763	0.0227	0.2706	0.2698	0.2791 ***
h=22	0.1270	0.1270	0.0394	0.0724	0.0724	0.0069

Note: AEX: Amsterdam Exchange index, BFX: Bell 20 Index, BVLG: Portugal Stock Index (PSI) All-Share Index, FCHI: Cotation Assistée en Continu (CAC) 40, FTMIB: Financial Times Stock Exchange (FTSE), Milano Indice di Borsa (MIB), FTSE: FTSE 100, GDAXI: Deutscher Aktienindex (DAX), IBEX: IBEX 35 Index, OMXC20: OMX Copenhagen 20 Index, OMXHPI: OMX Helsinki All Share Index, OMXSPI: OMX Stockholm All Share Index, OSEAX: Oslo Exchange All-share Index, SMSI: Madrid General Index, SSMI: Swiss Stock Market Index, STOXX50E: EURO STOXX 50 , BSESN: S&P BSE Sensex, HIS: HANG SENG Index, KS11: Korea Composite Stock Price Index (KOSPI), KSE: Karachi SE 100 Index, N225: Nikkei 225, NSEI: NIFTY 50, SSEC: Shanghai Composite Index, STI: Straits Times Index, DJI: Dow Jones Industrial Average, GSPTSE: S&P/TSX Composite index, IXIC: Nasdaq 100, MXX: IPC Mexico, RUT: Russel 2000, SPX: S&P 500 Index, BVSP: BVSP BOVESPA Index, and AORD: All Ordinaries. The forecasting gains. $FG = \left(\frac{RMSFE_0}{RMSFE_1} - 1\right) * 100$. where $RMSFE_0$ and $RMSFE_1$ are root mean squared forecast errors ($RMSFE_s$) of the benchmark HAR-RV model (Equation (1)) $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w.t} + \beta_m RV_{m.t} + \varepsilon_{t+h}$ and $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w.t} + \beta_m RV_{m.t} + \theta EMVID_t + \varepsilon_{t+h}$ the extended HAR-RV model (Equation (2)). RV is the daily realised volatility estimation of the international stock market index; EMVID is the newspaper-based uncertainty index due to infectious diseases. *** presents the significance of the MSF-F test statistics at the 1% level.

Comparing our findings for all the stock market indexes under analysis, moderate FGs, ranging from 0.03% to 0.10%, (in particular for the h = 1 and 5 horizons) are observed in the AEX, BSESN, BVSP, FCHI, FTMIB, FTSE, IXIC, KSE, NSEI, SMSI and STOXXSOE (in no particular order). Furthermore, our findings indicate that across all time horizons for HSI, h = 5 for GDAX1, h = 22 for IXIC, KSE and RUT, h = 1 and 5 for OSEAX and SPX, there is no forecast gain or loss. This indicates that in the lowest bound, we cannot infer any gain or loss in the latter international stock market indexes. Given these results, it is evident that the extended model, Equation (2), out-performs the basic model Equation (1). According to the MSE-F statistics[18], these results are significant[19] for h = 1, 5 and 22 for STI and h = 1 and 5 for AORD, BFX, BSESN, BVLG, KSE and RUT. We observe the same results for h = 1 for AEX, FCHI, IXIC, NSEI and STOXX50E, for h = 2 in FTSE and h = 3 for FTMIB[20]. The above results imply that uncertainty associated with infectious diseases has important information for predicting the future path of international stock markets' index RV in the short-, medium- and long-run.

Finally, we assess the forecasting power of the EMVID during the COVID-19 outbreak. With this purpose, our out-of-sample period covers the data from January 2020, and the in-sample period includes the same number of observations starting in 2018 to December 2019, i.e., we make the in- and out-of-sample periods of equal size. The period of the latter analysis incorporates all the phases of COVID-19, the first, second and third waves[21]. Having exclusively conducted our analysis based on the COVID-19 episode, the out-of-sample results indicate that the highest FG of 0.93% is for KSE (h = 1), Pakistan, followed by 0.91% for BVLG (h = 22), Portugal. That is, considering the information context of the daily newspaper-based index uncertainty related to infectious diseases based on the forecast accuracy of the RMSFE metrics during the COVID-19 episode, we can obtain the highest FG of 0.93% in the h = 1 model for KSE and 0.91% in the h = 22 model for BVLG. Our results also indicate an FG of 0.01% for AORD (h = 22) followed by 0.02% for STI (h = 22). In contrast, for MXX, N225, OSEAX and SSEC, across all time horizons, there is a forecasting loss, with the highest loss of 3.22% followed by 3.04% for OSEAX and NSEI in the h = 1-time horizon, respectively. The least forecast loss of 0.01% is evident in h = 1 for OMXC20. This implies that we can obtain the least forecasting loss of 0.01% in h = 1 for OMXC20. Masoud (2013) argue that stock markets are crucially linked to the economic growth in the short and long forecast horizon through improving liquidity, capital mobilisation, risk pooling management, and enhancing managers' and corporates' control. Therefore, efficient stock markets are seen a rendering a service that boost the economy. These results are significant at a 10% level of significance[22].

[18] The critical values at 10%, 5% and 1% are 3.951, 1.548 and 0.616.
[19] The MSE-F critical value is greater than the MSE-F statistics.
[20] It is worth noting that at 5% level of significance several stock markets index in our analysis are statistically significant except for the GDAX1, GSPTSE, HIS, BSESN, OMXHPI, OSEAX, SPX and SSEC.
[21] Also, this is the phase where the vaccination programmes rollout were implemented.
[22] The MSE-F critical value is greater than the MSE-F statistics. The critical values at 10%, 5% and 1% are 3.811, 1.583 and 0.693.

The KSE in Pakistan, KS11 in South Korea and STI in Singapore appear to be the most volatile stock market indexes during the COVID-19 period followed by the AORD in Sydney, Australia (Table A3.2)[23].

Concerning our findings, this chapter contributes to the existing literature showing that daily infectious diseases-related uncertainty or uncertainty related to pandemics and epidemics have the power to forecast international stock markets index RV in the short-, medium-, and long-horizon. Our chapter presents the first unique empirical evidence in the literature that relates the uncertainty derived from various types of infectious diseases with the predictability of realised volatilities of different international stock market indexes.

3.4. Discussion of the Results

In the context of the literature on forecasting stock market volatility (Poon and Granger 2003), the main contribution of this chapter relies on the predictive power of the EMVID variable for international stock market volatilities. While there is recent literature on the impact of COVID-19 on stock market volatility (Lyócsa and Molnár, 2020; Zaremba et al., 2020; Zhang et al., 2020), this chapter includes not only the recent COVID-19 outbreak but other pandemic episodes as well. While past infectious diseases (the H1N1 pandemic in 2009–2010, the Ebola outbreak in 2014–2016, the H5N1, MERS or SARV viruses, among others) have not been extensively considered to affect stock market volatilities, this chapter shows that the uncertainty related to these infectious diseases can have a significant impact on financial volatility.

Considering that different classes of market participants populate the stock market, where traders in the different classes differ in their sensitivity to information flows at different time horizons (that is, short-term traders versus long-term traders), we analyse the predictability of EMVID at different time horizons. The main results suggest that the predictive power of EMVID is mainly limited to short (h = 1) and medium (h = 5) horizons, suggesting that this variable seems to have only transitory effects on stock market volatility. This finding is in line with some literature that suggests that the impact of the COVID-19 pandemic on

[23] Based on the suggestion of any anonymous referee, we also conducted a similar analysis involving the forecastability of the available implied volatility indices of various countries, as listed in Table A3.1. As can be seen from the forecasting results reported in Table A3.2, using the same set-up as in Table 3.2, COVID-19 related uncertainty tend to produce higher forecasting gains for the implied volatilities of developed rather than emerging equity markets.

financial markets was lower and less persistent that observed, for example, after the 2008 Global Financial Crisis (Cunado et al., 2021).

Finally, it is interesting to analyse the international differences on the forecasting ability of EMVID in different stock markets. It is interesting to note that the most vulnerable stock markets to uncertainty related to infectious diseases are those in Singapore, Portugal and Netherlands. The different responses of international stock market volatilities to EMVID suggest that there are important international portfolio diversification and hedging opportunities in periods of infectious diseases.

3.5. Conclusions

The COVID-19 pandemic questioned the traditional 'safe haven' nature of the international stock market index. Given the heightened uncertainty related to infectious diseases, especially COVID-19, we contribute to the literature by predicting the future path of the international stock markets index RV amid daily newspaper-based index uncertainty related to infectious diseases (EMVID). A recursive estimation approach is adopted over the short-, medium-, and long-run using out-of-sample predictability. Our main findings could be summarized as follows. First, they indicate that EMVID plays a critical and significant role in predicting international stock markets index RV, which is in line with the recent literature on the impact of the COVID-19 pandemic on financial volatility, although in this chapter we extend our sample period to include uncertainty related to some other infectious diseases. Second, the results suggest that the highest predictive power of EMVID are found for short ($h = 1$) and medium ($h = 5$) horizons, while for the long-run, we find significant predictability power only for the stock markets in Singapore (STI) and Milan (FTMIB). Furthermore, the results suggest that the most vulnerable stock markets to EMVID are those in Singapore (in the short-, medium- and long-run), Portugal and The Netherlands (in the medium- and short-run). When only the COVID-19 episode is considered, the most vulnerable stock markets are those in Portugal and Pakistan.

Assessing the COVID-19 episode, the latter results were evident. These findings have important implications for investors, portfolio managers and policymakers. For example, the results suggest that there are international significant differences in the response of stock markets to infectious diseases, suggesting that international diversification opportunities can be found in the presence of episodes of infectious diseases. Since uncertainty related to infectious diseases will have different sectoral impacts, an analysis of the predictability of EMVID for sectoral stock market volatilities could help explore sectoral diversification opportunities. Future research will address this issue.

Lastly, our findings highlight the importance of accurate volatility forecasts when constructing hedging strategies in the financial market during high uncertainty as a result of pandemics and epidemics. In the future, we will extend our study on the agricultural commodity markets, to analyse the impact of the pandemic on issues of food security associated with price volatility.

Chapter 4

Infectious Diseases-Related Uncertainty and The Predictability of Foreign Exchange and Bitcoin Futures Realised Volatility[λ]

4.1. 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 behaviour, 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).

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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[24] (Clark et al., 2004; Asteriou et al., 2016; Senadza and Diaba, 2017), and hence, high-frequency forecast 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[25] 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)[26]. 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 chapter is the first to empirically examine the forecasting ability of uncertainty related to daily infectious diseases (EMVID) in predicting the realised volatility of foreign exchange and Bitcoin futures using the heterogeneous

[24] Exchange rate volatility affect growth through the following main channels, interest rate, trade and inflation (see Morina et al., 2020; Ramzan, 2021).
[25] National shutdowns, social distancing, government relief funds and other polities we implemented speedily to contain the spread of the virus.
[26] For example, lockdowns, wearing of masks, social distancing and most importantly, the social relief grant that were issued to economic agents.

autoregressive realised 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[27]. Specifically, 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 realised volatility (Gkillas et al., 2020). The Thesis 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, and then the Ebola pandemic that effectively took part from 2014 to 2016. Among other diseases that took place in our period of interest include the H5N1, MERS and SARS viruses.

As a proxy for daily infectious disease-related uncertainty, we employ the newspaper-based index by Baker et al. (2020b), which 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 realised volatility. To ensure precise and accurate forecasts and estimations, we employ intraday data. Second, our chapter adds value to the emerging literature of foreign exchange and cryptocurrency markets by predicting their realised 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 realised volatility). Third, we evaluate the predictability of EMVID for foreign exchange and Bitcoin realised 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 realised 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 chapter is as follows. In Section 4.2, we present the dataset and the HAR-RV model. Section 4.3 includes the forecasting results for foreign exchange and Bitcoin futures markets. Finally, Section 4.4 concludes.

[27] 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).

4.2. Dataset and Methodology

4.2.1. Dataset

We use intraday realised volatility data of foreign exchange and the 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 realised volatility data, Dacheng Xiu employs quasi-maximum likelihood estimates of a moving average model -MA(q)-. In our analysis, we select the 5 min realised volatility estimates as it contains the most precise and accurate information. Table 4.1 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 4.1. Selected Variables, Acronyms and Sample Coverage

Symbol	Future Index	Sample Period
1. AD	Australian Dollar	22 September 2008 - 17 June 2021
2. BP	British Dollar	22 September 2008 - 17 June 2021
3. CD	Canadian Dollar	22 September 2008 - 17 June 2021
4. JY	Japanese Yen	22 September 2008 - 17 June 2021
5. JYNM	Japanese Yen E-mini	27 July 2017 - 17 June 2021
6. NE	New Zealand Dollar	22 September 2008 - 17 June 2021
7. SF	Swiss Franc	22 September 2008 - 17 June 2021
8. URO	Euro FX	22 September 2008 - 17 June 2021
9. UROM	Euro FX E-mini	27 July 2017 - 17 June 2021
10. BTC	CME Bitcoin	18 December 2017 - 17 June 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.

4.2.2. Heterogeneous Autoregressive Realised 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 realised 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 realised variance on returns (Bonato et al., 2021; Wang et al., 2019). The benchmark HAR-RV model is given by

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \varepsilon_{t+h} \tag{1}$$

where RV is the realised volatility h-days ahead are represented by the h index with h = 1, 5 and 22; $RV_{w,t}$ is the average RV from day t - 6 to t - 1 and $RV_{m,t}$ 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

$$RV_{t+i} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta EMVID_t + \varepsilon_{t+i} \tag{2}$$

4.3. 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 chapter is to analyse the role EMVID plays in predicting the future path of foreign exchange and Bitcoin futures realised 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 4.2. 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 investigation is stationary when we look at the data plot (Fig. A4.1). Further stationarity test was conducted 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-RVand 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[28] proposed by McCracken (2007). Our out-of-sample forecasting gains (FG) are calculated using

$$FG = \left(\frac{RMSFE_0}{RMSFE_1} - 1\right) * 100 \tag{3}$$

Table 4.2. Structural Breakpoints.

Structural Breaks	Variables
September 2010	BP, CD and URO
October 2010	AD
November 2010	SF
October 2011	NE
July 2016	JYNM and UROM
July 2018	BTC
March 2021	JY

Note: AD: Australian Dollar, BP: British Dollar, CD: Canadian Dollar, JY: Japanese Yen, JYNM: Japanese Yen E-mini, NE: New Zealand Dollar, SF: Swiss Franc, URO: Euro FX, UROM: Euro FX E-mini, BTC: CME Bitcoin. Structural breakpoint detected using Bai and Perron (2003).

Table 4.3. Out-of-Sample Predictability

Horizon	$RMSFE_0$	$RMSFE_1$	FGs	$RMSFE_0$	$RMSFE_1$	FGs
	Panel 1: AD. 10/12/2010			Panel 2. BP: 9/14/2010		
h=1	0.0304	0.0302	0.8649***	0.0267	0.0257	3.8418***
h=5	0.0080	0.0079	1.1801***	0.0071	0.0067	6.1012***
h=22	0.0021	0.0018	13.7084***	0.0017	0.0017	3.9133***
	Panel 3: CD. 9/14/2010			Panel 4: JY. 3/21/2021		
h=1	0.0187	0.0187	-0.0214	0.0293	0.0298	-1.5967
h=5	0.0047	0.0047	0.9354***	0.0079	0.0075	4.2624***

[28] MSE-F = (T-R-h+1).dhat/MSE1

h=22	0.0008	0.0007	11.7647***	0.0012	0.0012	3.8494***
	Panel 5: JYNM. 7/27/2016			Panel 6: NE. 10/18/2011		
h=1	0.0442	0.0282	56.4489***	0.0313	0.0306	2.1152***
h=5	0.0088	0.0070	25.6597***	0.0084	0.0077	9.5010***
h=22	0.0033	0.0018	80.6593***	0.0020	0.0019	0.9824***
	Panel 7: SF. 11/04/2010			Panel 8: URO. 9/03/2010		
h=1	0.0535	0.0535	0.0168	0.0206	0.0206	-0.0340
h=5	0.0139	0.0139	0.0793***	0.0053	0.0053	0.2068***
h=22	0.0034	0.0034	0.1170***	0.0014	0.0014	0.2911***
	Panel 9: UROM. 7/01/2016			Panel 10: BTC. 7/18/2018		
h=1	0.0252	0.0252	-0.1111	0.4375	0.2672	63.7319***
h=5	0.0058	0.0057	0.5416***	0.3235	0.0718	350.8863***
h=22	0.0018	0.0015	21.2202***	0.0378	0.0182	108.1448***

Note: AD: Australian Dollar, BP: British Dollar, CD: Canadian Dollar, JY: Japanese Yen, JYNM: Japanese Yen E-mini, NE: New Zealand Dollar, SF: Swiss Franc, URO: Euro FX, UROM: Euro FX E-mini, BTC: CME Bitcoin. $FG = \left(\frac{RMSFE_0}{RMSFE_1} - 1\right) * 100$ computes the forecasting gains (FG), where the root mean squared 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 $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \varepsilon_{t+h}$; and the extended HAR-RV model is given by $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta EMVID_t + \varepsilon_{t+h}$. Daily realised volatility for foreign exchange and Bitcoin futures is denoted as RV and EMVID represent 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 4.3 together with their respective FGs. According to our out-of-sample results, the Bitcoin futures index realised volatility presents the highest forecast gain of 350.89% in the h = 5-day horizon followed by a 108.14% forecast gain in the h = 22-day horizon, whereas the JYNM futures realised volatility observes an 80.66% forecast gain in the h = 22-day 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).

Table 4.4. Out-of-Sample FG for the COVID-19 Episode.

Horizons	**$RMSFE_0$**	**$RMSFE_1$**	**FGs**	**$RMSFE_0$**	**$RMSFE_1$**	**FGs**
	Panel 1: AD. 01/02/2019			Panel 2: BP. 01/02/2019		
h=1	0.0352	0.0332	6.2477***	0.0232	0.0235	-1.3083
h=5	0.0096	0.0083	15.9706***	0.0079	0.0061	29.8627***
h=22	0.0024	0.0022	9.8206***	0.0020	0.0017	22.3827***
	Panel 3: CD. 01/02/2019			Panel 4: JY. 01/02/2019		
h=1	0.0178	0.0181	-1.5015	0.0200	0.0199	0.4278***

h=5	0.0045	0.0044	2.2887***	0.0050	0.0049	2.7071***
h=22	0.0009	0.0008	9.6031***	0.0010	0.0010	1.4735***
	Panel 5: JYNM. 01/02/2019			Panel 6: NE. 01/02/2019		
h=1	0.0233	0.0233	0.1889	0.0311	0.0311	0.0322
h=5	0.0066	0.0059	12.1827***	0.0092	0.0079	16.8695***
h=22	0.0017	0.0016	9.1201***	0.0021	0.0021	1.9580***
	Panel 7: SF. 01/02/2019			Panel 8: URO. 01/02/2019		
h=1	0.0249	0.0175	42.4267***	0.0151	0.0139	8.3663***
h=5	0.0044	0.0043	1.3689***	0.0042	0.0036	17.3039***
h=22	0.0033	0.0012	184.7414***	0.0010	0.0010	2.6178***
	Panel 9: UROM. 01/02/2019			Panel 10: BTC. 01/02/2019		
h=1	0.0191	0.0178	7.0156***	0.4177	0.2659	57.1161***
h=5	0.0049	0.0044	13.3074***	0.2626	0.0699	275.6125***
h=22	0.0012	0.0012	4.4351***	0.0354	0.0182	94.7235***

Note: AD: Australian Dollar, BP: British Dollar, CD: Canadian Dollar, JY: Japanese Yen, JYNM: Japanese Yen E-mini, NE: New Zealand Dollar, SF: Swiss Franc, URO: Euro FX, UROM: Euro FX E-mini, BTC: CME Bitcoin. In the COVID-19 period, the forecast gains are computed as follows, $FG = \left(\frac{RMSFE_0}{RMSFE_1} - 1\right) * 100$ the root mean squared forecast errors ($RMSFE_S$) for the benchmark model (equation 1) is represented as $RMSFE_0$, and that of the extended model is shown as $RMSFE_1$ (equation 2). RV denotes the daily realised 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.

The Swiss Franc futures RV 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 losses 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 a 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.

According to Korkmaz (2013), there is a causality from exchange rate towards economic growth. Consequently, our findings provide evident that an efficient foreign exchange rate market through the use of relevant hedging instruments in important for the performance of our economies. Given the traditional currency threats, especially the US dollar and advancement of technology “Internet of Thinks’, virtual currency is bound to start taking over (Seetharaman et al., 2017). Our findings in the cryptocurrency market as indicated by BTC provides evidence that they can be safely utilised in the trading of goods and services to boost economic growth.

4.4. 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 chapter contributes to the literature of foreign exchange and Bitcoin by forecasting their realised 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 realised 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. Next, 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 on the food supply chain.

Chapter 5

Forecastability of Agricultural Commodity Futures Realised Volatility with Daily Infectious Disease-Related Uncertainty[ϒ]

5.1. Introduction

The disruption of food supply chains from COVID-19 lockdowns around the world triggered a tremendous interest in understanding the “safe haven” attribute of agricultural commodity futures (Ji et al. 2020; Sifat et al. 2021; Rubbaniy et al. 2022; Zhang and Wang 2022), raising concerns about the attractiveness of these vehicles in commodity options trading, global supply chain risk management[29], strategic asset allocations, and regulators’ supervision of inflation risk during infectious disease-related uncertainty.

In 2015, the United Nations set 17 Sustainable Development Goals (SDGs) that were aimed at improving the standard of living in the world by 2030 (SDSN 2021). Among these SDGs are those of no poverty (SDG1) and zero hunger (SDG2) by 2030. The COVID-19 outbreak imposed the greatest threat to these goals and adversely affected some of the developing progress in achieving them when governments imposed measures such as lockdowns[30] to contain the spread of the virus (Khan et al. 2020). In addition to the lost lives, Béné (2020) emphasised that the main effect of COVID-19 was driven by mobility restrictions by governments, which led to a subsequent loss of income and reduction in purchasing power, especially for low-income individuals and households. The restricted movement between countries (see McBryde et al. 2022) triggered demand and supply shocks (Guerrieri et al. 2022). This threatened food security, the most crucial aspect of sustainable development and economic growth in different parts of the world (Arndt et al.2020; Mardones et al. 2020; O’Hara and Toussaint 2021). Empirically, approximately 265 million people were affected by food insecurity in 2020, which is a 135 million increase from the COVID-19 outbreak[31] (Food Security Information Network 2020).

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[29] The profitability of businesses heavily depends on risk management strategies to hedge futures cash flow uncertainty.

[30] Lockdowns reduced the movement of goods and services and even brought some to zero, i.e., movements of imports and exports.

[31] In Afghanistan, the Democratic Republic of the Congo, Ethiopia, Haiti, Nigeria, South Sudans, The Sudan and Yemen around 74 million people were classified under emergency due to the need of food.

The interest of our chapter in commodity markets is driven by food security and their more dramatic price fluctuations compared with other financial markets (Hák et al. 2016). If we think of agricultural commodities, for instance, the production of goods is not uniform throughout the year (de Keizer et al. 2017). Crops, for example, grow in a certain season and are usually harvested a few times a year, and it can often be unpredictable up to a certain point whether the crops will turn out good or bad. The weather conditions have a big effect on these outcomes; however, we may have other unpredictable factors such as pesticides (Tudi et al. 2021). These kinds of fluctuations are a problem for commodity producers, investors, and portfolio managers. Moreover, the COVID-19 outbreak led to high volatility as a result of the high unprecedented uncertainties in the financial market[32], especially in the commodity markets. Therefore, it is crucial for investors and portfolio managers to mitigate or offset such risk by finding "safe haven" commodity futures during times of infectious diseases.

In times of financial market uncertainties from global crises such as infectious diseases, especially the recent coronavirus pandemic, typically used portfolio risk management strategies are likely to default (Umar and Gubareva 2020; Harjoto et al. 2021). This may result in extreme market volatility because of high trades. More precisely, the disastrous COVID-19 pandemic prompted a high level of uncertainty in the commodity markets although the reaction of such markets differed across countries and traded commodity brackets. For instance, commodity-dependent countries rely heavily on exports and imports as low-and middle-income countries; as a result, they experienced a strong adverse reaction in their markets (Tröster 2020). On the other hand, Borgards et al. (2021) showed that the reaction of agricultural (soft) and metal commodities to the pandemic was minimal except for special treasures such as gold. In addition, Zhang and Hamori (2021) argued that the effects of COVID-19 on the financial markets are more significant compared to other historical shocks such as the 2008 financial crisis, droughts, and floods, although their short-, medium-, and long-run impact is uncertain.

In this context, the objective of our chapter is to investigate, for the first time, the predictive ability of daily infectious disease-related uncertainty (EMVID) for agricultural future realised volatilities utilising the heterogeneous autoregressive realised variance (HAR-RV) model. The main attribute of the HAR-RV model is its ability to use volatilities from

[32] Liao et al. (2018) noted the following three channels through which the fluctuation in the financial market can impact com-modity prices: macro-economy reflection channel, financial market information transmission channel, and market sentiment contagion channel.

different time horizons to predict the realised volatility on returns. The model contains the heterogeneous market hypothesis, which states that market participants in their different categories react differently to information flow in the short, medium, and long-run (Müller et al. 1997). For example, speculators and traders in the market are more concerned about short-term investments, while investors are more interested in long-term investments. Conventionally, the time-varying volatility is modelled, and the fit is assessed using various generalised autoregressive conditional heteroscedastic (GARCH) models, under which the conditional variance is a deterministic function of model parameters and past data. Alternatively, researchers have also considered stochastic volatility models, where volatility is a latent variable that follows a stochastic process. These models rely on daily data, and not intraday data as used to obtain RV, which in turn is known to be a more accurate estimate of the latent process of volatility due to the richness of the underlying intraday data (McAleer and Medeiros 2008).

There are a number of studies on the nexus between commodity returns and infectious diseases, especially since the incidence of the COVID-19 pandemic (See Balcilar et al. 2022; Long and Guo 2022; Akyildirim et al. 2022; Nascimento et al. 2022; Daglis et al. 2020; Umar et al. 2022; Cariappa et al. 2022; Chen et al. 2022; Shruthi and Ramani; 2021); Gutierrez et al. 2022; Ayyildiz 2022). However, the current study makes key contributions to the existing literature. First, the focus of existing studies was mainly on the COVID-19 pandemic, while the current study focuses on infectious disease-related uncertainty (EMVID). Secondly, existing studies used daily data for commodity returns, while we use the realised volatility of intraday agricultural commodity futures. The employed intraday data contains information that may result in more accurate and precise estimates and forecasts across different time horizons. Thirdly, relative to existing studies, we analyse the out-of-sample power of EMVID for more (15) agricultural commodity futures (i.e., BO, CC, C, CT, KC, OJ, SB, SM, S, W, FC, LB, LC, LH, and O) (Table A1). The data coverage of uncertainty related to infectious diseases not only covers the COVID-19 episode, but also includes other infectious diseases such as Ebola, H1N1, H5N1, MERS, or SARS viruses and the recent monkeypox. We use the newspaper-based index by Baker et al. (2020) as a proxy for infectious disease-related uncertainty. The index is derived from the daily equity market volatility (EMV) hosted in the Chicago Board Options Exchange (CBOE) volatility index. This index is robust for a statistical model aimed at forecasting the realised volatility of agricultural commodity futures. Furthermore, this chapter contributes to the literature on agricultural commodity futures in that it predicts its realised volatility computed from 5 min intervals utilising the modified heteroscedasticity autoregression model by Corsi (2009). In particular, the basic HAR-RV model is extended by adding the daily infectious disease-related uncertainty (EMVID) variable and then examining its predictive power on the variables of interest (agricultural commodity futures). Furthermore, we employ recursive out-of-sample predictability of EMVID for the realised volatility of 15 agricultural commodity futures in the short, medium, and long run. In sum, our study is holistic and novel in terms of the wider coverage of the infectious disease range, the focus on intraday realised volatility of a large number of agricultural commodities, the focus on the out-of-sample predictability of EMVID, and the uniqueness of the modified HAR-RV model used, allowing us to conduct short-, medium-, and long-run fore-cast analysis. To the best of our knowledge, we are not aware of any study that has examined the out-of-sample predictability of EMVID for the intraday volatility of agricultural commodities using the HAR-RV model. This analysis has important implications for portfolio managers in their portfolio diversification possibilities given uncertainties from infectious diseases.

The remaining part of our chapter is structured as follows: Section 5.2 describes the data and methodology. Section 5.3 presents the empirical results. Section 5.4 concludes the chapter.

5.2. Data and Methodology

5.2.1. Data

Data on the realised volatility (RV) of commodity futures were sourced directly from the University of Chicago Booth School of Business Risk Lab under the maintenance of Professor Dacheng Xiu. This series is publicly available at https://dachxiu.chicagobooth.edu/#risklab.com (assessed on 27 April 2022). The highest-frequency available trades were collected and cleaned using the prevalent national best bid and offer (NBBO) that is available every second. The RV estimation procedure was computed using the quasi-maximum likelihood estimation of volatility (QMLE) from moving average models MA(q), using nonzero returns of transaction prices sampled up to the earliest available frequency for days with at least 12 observations (see Xiu 2010). In choosing the best MA(q), we used the Akaike information criterion. We also employed the 5min RV estimates for our analysis.

The index on dairy infectious disease-related uncertainty (EMVID) is publicly accessible at http://policyuncertainty.com/infectious_EMV.html (accessed on 27 April 2022). This index was developed by Baker et al. (2020) using a newspaper-based infectious disease equity market volatility tracker. In this chapter, we use the EMVID data from as early as 22 September 2008 to 27 April 2022 for BO, CC, C, CT, KC, OJ, SB, SM, S, and W RVs, and then from 27 July 2015 to 27 April 2022 for FC, LB, LC, LH, and O RVs (Table A1). EMVID is based on the following four textual analysis terms: E, economic, economy, financial; M, "stock market", equity, equities, "standard and poor"; V: volatility, volatile, uncertain, uncertainty, risky; ID: H1N1, H5N1, MERS, SARS, Ebola pandemic, epidemic, virus, diseases, and coronavirus. In each of the E, M, V, and ID terms, a daily count of at least one term over 3000 US newspaper articles were computed into the EMVID index. On the same day, Baker et al. (2020) multiplicatively re-scaled the final series to equal the level of the VIX through the overall EMV index; then, the EMVID index was scaled to total the EMV articles. Our data range varied from the earliest data available to the latest date from our estimation. More interestingly, our data period covers the COVID-19 virus and other economic uncertainties such as the global financial crisis. Given daily infectious disease-related uncertainty, the EMVID index is the only proxy for uncertainty related to various infectious diseases.

5.2.2. Methodology: Heterogeneous Autoregressive Realised Variance (HAR-RV) Model

To realise the main objective of our chapter, we conducted the out-of-sample predictability analysis using the Corsi (2009) HAR-RV model. The key feature of our model is its ability to reproduce the important properties contained in financial data in their respective time intervals while remaining simple (Wang et al. 2019; Gkillas et al. 2020). These properties include fat tails, long memory, multi-scaling behaviour, and self-similarity. The basic HAR-RV model is

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w.t} + \beta_m RV_{m.t} + \varepsilon_{t+h} \quad (1)$$

where realised volatility (RV) h days ahead is represented by the h index (in our chapter, h =1, 5, and 22);$RV_{w.t}$ represents the average RV from day t–6 to t–1, whereas $RV_{m.t}$ depicts the mean RV from day $t-22$ to day $t-6$. We then add the EMVID index to the benchmark HAR-RV model to capture the interest of our chapter. β_0 is a constant, ceteris paribus. $\beta_{d,w\ and\ m}$ are our respective coefficients for the short-, medium-, and long-run RV, while ε_{t+h} is our error term. The extended HAR-RV model (θ is the coefficient for daily infectious disease-related uncertainty) is

$$RV_{t+i} = \beta_0 + \beta_d RV_t + \beta_w RV_{w.t} + \beta_m RV_{m.t} + \theta EMVID_t + \varepsilon_{t+i} \quad (2)$$

5.3. Empirical Results

In this chapter, we focus on the out-of-sample predictability of the realised volatility (RV) of commodity traded futures, “the softs”; that is, we access the role that daily infectious disease-related uncertainty (EMVID) plays in predicting the future path of our variables of interest. Campbell (2008) and Bouri et al. (2020a) argued that the best test for any predictive model relies on its out-of-sample performance in terms of any econometric and predictability. We employ an out-of-sample recursive approach from the earliest data available to the latest data for our estimation. The data plots on the variables under investigation in Figure A5.1 move around the mean with a sharp positive shock that quickly goes back to the mean in the first quarter of the COVID-19 pandemic, especially for our independent variable. Our out-of-sample multiple structural breakpoints tests were determined using the HAR-RV model under the Bai and Perron (2003) test of 1 to M globally determined breaks and UDMax and WDMax statistics.

Table 5.1. Structural Breakpoints.

Date	Symbol	Names
September 2010	KC	Coffee “c” futures
October 2010	C, CT,and S	Corn futures, cotton #2 futures, and soybean futures
November 2010	BO and LC	Soybean oil futures and live cattle futures
December 2010	OJ and SB	Orange juice futures and sugar #11 futures
March 2011	CC and SM	Cocoa futures and soybean meal futures
October 2011	W	Wheat futures cbot
August 2016	FC, LB, and O	Feeder cattle futures, lumber futures, and oats futures
October 2016	LH	Lean hogs futures

As tested by the multiple structural breakpoints test, Table 5.1 depicts that most agricultural commodity futures experienced multiple structural breaks in 2010. More precisely, corn (C), cotton #2 (CT), and soybean (S) futures experienced a structural breakpoint in October 2010, followed by soybean oil (BO) and live cattle (LC) futures in November 2010. The orange juice (OJ) and sugar #11 (SB) futures had a structural breakpoint in December 2010. In September

2010, the coffee “C” (KC) experienced a breakpoint. Furthermore, cocoa (CC) and soybean meal (SM) futures had a structural breakpoint in March 2011, and wheat futures CBOT (W) experienced a breakpoint in October 2011. Lastly, the feeder cattle (FC), lumber (LB) and oats (O) futures had a structural breakpoint in August 2016, and the lean hogs (LH) futures experienced a breakpoint in October 2016. The important basis of these multiple structural break-points involves factors such as food price peaking, reduction in grain stock, low-interest rates, and the depreciation of the United States (US) dollar (Headey 2011). Export restrictions, droughts, demand surges, trade shocks, and climate change are among other factors contributing to the global food crisis (see Falkendal et al. 2021; Lieber et al. 2022).

Next, we compute the root-mean-squared forecast errors (RMSFEs) for the benchmark and extended h=1, 5, and 22 HAR-RV models using the above multiple structural breakpoints models. Since our primary aim is to forecast, lower RMSFEs in our recursive out-of-sample estimated from the earliest experienced breakpoint in all the variables of interest would represent a better-performing model. For forecast accuracy, we employ the McCracken (2007) MSE-F test[33]. The out-of-sample forecast gains (FG) were calculated using the following formula:

$$FG = \left(\frac{RMSFE_0}{RMSFE_1} - 1\right) * 100 \quad (3)$$

where $RMSFE_0$ denotes the RMSFEs for the benchmark HAR-RV model, while the RMSFEs for the extended HAR-RV model are presented by $RMSFE_1$. Positive or negative FGs indicate the gains or losses in percentage (Equation (3)).

According to our out-of-sample results in Table 5.2, the highest forecast loss of 0.28% was for the lumber futures (LB), followed by 0.26% forecast loss for soybean oil futures (BO) in the short run (h=1), and then 0.25% in the medium run (h=5) in the BO. This implies that taking the information context of the daily infectious disease-related uncertainty (EMVID) into consideration using the forecast accuracy of the RMSFE metrics within our period of interest, an econometrician can obtain the highest forecast loss of 0.28% for LB (h=1), followed by 0.26% and then 0.25% for BO h=1 and h=5, respectively. Our results also indicate that the coffee “C” (h=22) and oat futures (O) (h=5) remained constant, i.e., there was no forecast gain or loss. However, the lowest forecast loss of 0.01% was in the oat futures h=1 model, followed by 0.02 for wheat futures CBOT (W) in the h=22 model. This suggests that considering the

[33] MSE-F = (T-R-h+1).dhat/MSE1

information context of uncertainty associated with infectious diseases based on the forecast accuracy of the RMSFE metrics, an econometrician would not be able to obtain any forecast gain or loss for KC(h=22) and O (h=5), but could at least obtain a minimal forecast loss of 0.01% for O (h=1), followed by 0.02% for W (h=22). Considering the whole sample period, these negative FGs also imply that EMVID adds no value in forecasting the realised volatility of our commodity futures. Therefore, the MSE-F test cannot be significant it is a one-sided test associated with whether the unrestricted model does better than the restricted one.

Table 5.2. Full Out-of-Sample Forecasting Gains

Horizon	$RMSFE_0$	$RMSFE_1$	FGs	$RMSFE_0$	$RMSFE_1$	FGs
	Panel 1: BO: 11/18/2010			Panel 2: CC: 3/08/2011		
1	0.0415	0.0416	−0.2643	0.0497	0.0497	−0.0282
5	0.0107	0.0107	−0.2528	0.0131	0.0131	−0.0229
22	0.0027	0.0027	−0.0741	0.0033	0.0033	−0.0302
	Panel 3: C: 10/29/2010			Panel 4: CT: 10/12/2010		
1	0.0781	0.0781	−0.0717	0.0632	0.0633	−0.1201
5	0.0202	0.0202	−0.0594	0.0165	0.0165	−0.0666
22	0.0049	0.0049	−0.0616	0.0041	0.0041	−0.0978
	Panel 5: FC: 8/18/2016			Panel 6: KC: 9/14/2010		
1	0.0503	0.0503	−0.0875	0.0578	0.0578	−0.1124
5	0.0129	0.0129	−0.0310	0.0152	0.0152	−0.0721
22	0.0018	0.0018	−0.1103	0.0038	0.0038	0.0000
	Panel 7: LB: 8/19/2016			Panel 8: LC: 11/04/2010		
1	0.1757	0.1762	−0.2798	0.0531	0.0532	−0.1937
5	0.0455	0.0455	−0.1383	0.0131	0.0131	−0.0915
22	0.0113	0.0114	−0.1674	0.0035	0.0035	−0.1442
	Panel9: LH: 10/11/2016			Panel10: OJ: 12/29/2010		
1	0.0740	0.0740	−0.0811	0.1239	0.1240	−0.0468
5	0.0184	0.0184	−0.0760	0.0324	0.0324	−0.0309
22	0.0049	0.0049	−0.1233	0.0078	0.0078	−0.0385
	Panel 11: O: 8/17/2016			Panel 12: SB: 12/30/2010		
1	0.1394	0.1394	−0.0065	0.0570	0.0570	−0.0526
5	0.0366	0.0366	−0.0027	0.0148	0.0148	−0.0271
22	0.0087	0.0087	−0.0345	0.0037	0.0037	−0.0540
	Panel 13: SM: 3/21/2011			Panel 14: S: 10/21/2010		
1	0.0536	0.0536	−0.0280	0.0461	0.0461	−0.0390
5	0.0139	0.0139	−0.0359	0.0120	0.0120	−0.0334
22	0.0034	0.0034	−0.0291	0.0029	0.0029	−0.0344
	Panel15: W: 10/03/2011					
1	0.0683	0.0684	−0.0702			
5	0.0183	0.0184	−0.0436			
22	0.0046	0.0046	−0.0219			

Note: BO: Soybean Oil Futures, CC: Cocoa Futures, C: Corn Futures, CT: Cotton #2 Futures, FC: Feeder Cattle Futures, KC: Coffee "c" Futures, LB: Lumber Futures, LC: Live Cattle Futures, LH: Lean Hogs Futures, OJ: Orange Juice Futures, O: Oats Futures, SB: Sugar #11 Futures, SM: Soybean Meal Futures, S: Soybean Futures, W: Wheat Futures cbot. $FG = \left(\frac{RMSFE_0}{RMSFE_1} - 1\right) \times 100$ was the formula used to calculate the forecasting gains (FG), where $RMSFE_0$ stands for the root-mean-squared forecast errors ($RMSFE_S$) for the benchmark model, and $RMSFE_1$represents the $RMSFE_S$ for the extended HAR-RV model. $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \varepsilon_{t+h}$ is the equation for the benchmark HAR-RV model, and $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta EMVID_t + \varepsilon_{t+h}$is the equation for the extended HAR-RV model. RV depicts the daily realised volatility for agricultural commodity futures, while the daily infectious disease-related uncertainty is shown by EMVID.

Across all economic agents, the interest in searching for "safe haven" vehicles given infectious disease-related uncertainty was triggered by the COVID-19 outbreak; therefore, it is crucial to assess the impact of EMVID within the COVID-19 period. As the primary purpose of this chapter, we conducted a recursive out-of-sample estimation from January 2020 to the earliest period of our estimation and computed the in-sample period including the same number of observations. That is, we performed in- and out-of-sample observations. This period incorporates all phases of COVID-19. Within the COVID-19 episode, our results in Table 5.3 depict that the cocoa futures (CC) had the highest FG of 265.12% in the h=22 model, followed by 119.38% for oats futures in the h=22 model, and then 91.40% for sugar #11 futures (h=1). This implies that, by incorporating the information context of infectious disease-related uncertainty such as COVID-19 using the forecast accuracy of the RMSFE metrics, an econometrician could acquire the highest FG of 265.12% for CC (h=22), followed by 119.37% for O (h=22), and then 91.40 for SB (h=1). Furthermore, within the same episode, the lowest forecast gains of 0.70%, 1.49%, and 1.68% were evident in the SM (h=5), SB (h=22), and SM (h=1), respectively. These mean that considering COVID-19-related uncertainty and the forecast accuracy RMSFE metrics, an econometrician could obtain the lowest FGs of 0.70% in SM (h=5), followed by 1.49% for SB (h=22), and then 1.68% for SM (h=1). According to the MSE-F critical values[34], these results were statistically significant at a 1% level of significance except for BO in the h=1 and h=5 models. Also, our results provide evidence on the positive future perspective investors have on the economy because commodity future contract are inherently forward-looking and embed investor expectations of the future macroeconomic environment (Ye el at., 2019).

Most importantly, the results of our out-of-sample in the COVID-19 episode indicate the extent to which trade openness can be affected by a national shutdown given infectious

[34] MSE-F critical values: 3.584, 1.548, and 0.751.

diseases. Specifically, the supply shock triggered food insecurity; as a result, there was a high willingness to hedge against such risks.

Table 5.3. COVID-19 Episode Out-of-Sample Forecasting Gains

Horizon	RMSE$_0$	RMSEE $_1$	FGs	RMSE$_0$	RMSEE $_1$	FGs
	Panel 1: BO: 01/02/2019			Panel 2: CC: 01/02/2019		
1	0.0593	0.0668	−11.2464	0.0683	0.0441	54.9028 ***
5	0.0151	0.0164	−8.0490	0.0167	0.0113	48.3345 ***
22	0.0039	0.0036	8.8284 ***	0.0107	0.0029	265.1210 ***
	Panel 3: C: 01/02/2019			Panel 4: CT: 01/02/2019		
1	0.1225	0.0743	64.7963 ***	0.1141	0.0673	69.4641 ***
5	0.0336	0.0195	72.1085 ***	0.0195	0.0172	13.8156 ***
22	0.0058	0.0049	18.4884 ***	0.0046	0.0044	4.2970 ***
	Panel 5: FC: 01/02/2019			Panel 6: KC: 01/02/2019		
1	0.0619	0.0523	18.4753 ***	0.0787	0.0703	11.9315 ***
5	0.0203	0.0169	19.9965 ***	0.0245	0.0182	34.4523 ***
22	0.0026	0.0023	11.3804 ***	0.0050	0.0047	6.8548 ***
	Panel 7: LB: 01/02/2019			Panel 8: LC: 01/02/2019		
1	0.2823	0.2492	13.3014 ***	0.1038	0.0737	40.7548 ***
5	0.0861	0.0641	34.3329 ***	0.0239	0.0179	33.5645 ***
22	0.0165	0.0161	2.4484 ***	0.0050	0.0048	2.9724 ***
	Panel9: LH: 01/02/2019			Panel10: OJ: 01/02/2019		
1	0.0977	0.0871	12.2664 ***	0.1552	0.1310	18.5122 ***
5	0.0302	0.0211	43.3042 ***	0.0408	0.0335	21.8513 ***
22	0.0063	0.0059	6.7586 ***	0.0124	0.0079	56.6002 ***
	Panel 11: O:01/02/2019			Panel 12: SB:01/02/2019		
1	0.2343	0.1449	61.6987 ***	0.0990	0.0517	91.4020 ***
5	0.0378	0.0370	2.2160 ***	0.0199	0.0131	52.1473 ***
22	0.0197	0.0090	119.3689 ***	0.0034	0.0034	1.4784 ***
	Panel 13: SM: 01/02/2019			Panel14: S: 01/02/2019		
1	0.0517	0.0508	1.6788 ***	0.0623	0.0458	36.0493 ***
5	0.0133	0.0133	0.7018 ***	0.0152	0.0118	27.9527 ***
22	0.0060	0.0035	72.6407 ***	0.0030	0.0030	0.0000 ***
	Panel15: W: 01/02/2019					
1	0.1612	0.0935	72.4723 ***			
5	0.0429	0.0257	66.8597 ***			
22	0.0084	0.0063	32.7129 ***			

Note: BO: Soybean Oil Futures, CC: Cocoa Futures, C: Corn Futures, CT: Cotton #2 Futures, FC: Feeder Cattle Futures, KC: Coffee "c" Futures, LB: Lumber Futures, LC: Live Cattle Futures, LH: Lean Hogs Futures, OJ: Orange Juice Futures, O: Oats Futures, SB: Sugar #11 Futures, SM: Soybean Meal Futures, S: Soybean Futures, W: Wheat Futures cbot. $FG = \left(\frac{RMSFE_0}{RMSFE_1} - 1\right) \times 100$ was the formula used to calculate the forecasting gains (FG), where $RMSFE_0$ stands for the root-mean-squared forecast errors ($RMSFE_S$) for the benchmark model, and $RMSFE_1$represents the $RMSFE_S$ for the extended HAR-RV model. $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \varepsilon_{t+h}$ is the equation for the benchmark HAR-RV model, and $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta EMVID_t + \varepsilon_{t+h}$is the equation for the extended HAR-RV model. RV depicts the daily realised volatility for agricultural commodity futures, while the daily infectious disease-related uncertainty is shown by EMVID. The MSE-F test denotes the level of significance at the 1% level, as represented by ***.

5.4. Conclusion

Given food insecurity problems as a result of the COVID-19 lockdowns around the world, we investigated the forecasting ability of daily infectious disease-related uncertainty (EMVID) with respect to the realised volatility of agricultural commodity traded futures. We employed the heterogeneous autoregressive realised variance (HAR-RV) model by Corsi (2009) on 15 commodity-traded futures. Considering our recursive out-of-sample estimation approach in the short, medium, and long-run within the COVID-19 episode, it is evident that cocoa futures (CC) had the highest FG of 265.12% in the long run (h=22), followed by oat futures (O) with 119.38% FG in h=22, and then 91.40% FG for sugar #11 (SB) in the short run (h=1). This implies that considering the information context of the forecasting accuracy for RMSFE metrics within the COVID-19 period, an econometrician could obtain the highest FG of 265.12% in CC h=22, followed by 119.38% for O h=22, and then 91.40% for SB h=1. An econometrician could also obtain the lowest FG of 0.70%, followed by 1.49% and 1.68% in SM h=5, SB h=22, and SM h=1, respectively.

Our results within the COVID-19 episode suggest that EMVID plays an important role in predicting the future path of agricultural commodity futures. These findings have important policy implications for portfolio managers and investors in their search for safe investment or diversification options in the financial market. These results are robust as suggested by McCracken's (2007) MSE-F test. The COVID-19 pandemic is the worst crisis the world had seen; therefore, there are limited related studies and measures or indices for COVID-19. Furthermore, the pandemic already aggravated existing food insecurity problems and other global challenges; hence, we cannot blame the volatility of this asset class under review solely on the pandemic. In the future, we expect to extend our study to other brackets of agricultural commodities such as those in the metal bracket.

Chapter 6

Contagious Diseases and Gold Returns: Over 700 Years of Evidence from Quantile Regressions[#]

6.1. Introduction

In line with the literature on rare disaster risks and gold returns (Barro and Mishra, 2016; Salisu et al., forthcoming), quite a few recent papers, for example, Ali et al. (2020), Ji et al. (2020), Salisu et al. (2021), Tanin et al. (2021), Wang (2021) and Zhang et al. (2022), relate movements in gold prices with the number of, and news about, global infections and fatalities, as well as with metrics of macroeconomic uncertainties, resulting from the spread of the COVID-19 pandemic. In general, these studies tend to suggest that gold returns are affected positively in a statistically significant manner, or are, including its downside risks, statistically unaffected by infections, fatalities or uncertainties. In other words, gold can act as a safe haven or even a hedge against the risks produced by the coronavirus.

In this chapter, we build on this line of research from a historical perspective, by analysing the (predictive) impact of the global probability of fatality (i.e., number of deaths relative to the population) due to contagious diseases on (real) gold (log-)returns over the period 1258 to 2020, given that 1257 corresponds to the first available data point for real gold prices. In the process, we go beyond the COVID-19 episode covered by existing studies (e.g., Bouri et al., 2021), and consider as many as 62 outbreaks of contagious diseases starting with the Black Death in 1331.

From an econometric perspective, we use a quantile regression approach, as well as the benchmark linear regression model. We argue that, due to non-linearity and non-normality patterns, which we show to exist overwhelmingly in our dataset based on formal statistical tests, a linear regression approach might not be adequate for exploring the ability of the probability of fatality due to an outbreak of contagious disease to predict real gold returns. A quantiles-based method gives us a more complete characterization of the entire conditional distribution of real gold returns through a set of conditional quantiles, rather than only its conditional mean, as is the case with the standard linear regression approach. Looking at just

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[#] This chapter has been published as: Bouri, E., Gupta, R., Nel, J. and Shiba, S., 2022. Contagious diseases and gold: Over 700 years of evidence from quantile regressions. *Finance Research Letters*, 50, p.103266.

the conditional mean of real gold returns is likely to hide interesting characteristics, and can lead us to conclude that a covariate, in our case probability of fatalities due to rare disaster events, i.e., outbreaks of contagious diseases, has poor explanatory power, while it actually contains valuable information for certain parts of the conditional distribution of real gold returns. Furthermore, in terms of modelling non-linearity, unlike the Markov-switching and smooth threshold models, we do not need to specify the number of regimes of real gold returns (for instance, bear and bull) in an ad hoc fashion with the quantiles-based approach. This is because, weak periods in the gold market correspond to low quantiles or the left tail of the returns distribution, while strong periods are captured by the high quantiles or right tail of the same. Note that, since the quantile regression covers the entire conditional distribution, which captures various states of the gold market, it adds an inherent time-varying component to the estimation process.

To the best of our knowledge, this is the first chapter to formally study the empirical relationship between real gold returns and probability of fatality due to contagious diseases using a quantiles-based econometric method spanning the longest possible available history of these two variables, and hence avoiding any sample selection bias in the process, while providing a complete picture of the evolution of the gold market in the wake of deaths from outbreaks of contagious diseases. Understandably, our findings should be of immense value to the portfolio allocation decisions of investors, if we detect evidence of a quantile-specific impact of the probability of fatality resulting from contagious diseases based on data covering the entire history of the gold market, especially given that waves of COVID-19 continue to raise the global death toll on a daily basis. The remainder of the chapter is organized as follows: Section 6.2 outlines the data and the methodologies, while Section 6.3 presents the empirical results, with Section 6.4 concludes the chapter.

6.2. Data and Methodologies

6.2.1. Data

For the price of gold, we use annual data of nominal prices (in British pounds) of gold starting in 1257, retrieved from Measuring Worth.[35] The nominal price of gold is transformed into its real counterpart by

[35] https://www.measuringworth.com/.

deflating with the Consumer Price Index (CPI) of the UK derived from a database maintained by the Bank of England called: "A Millennium of Macroeconomic Data for the UK" until 2016,[36] and for the remainder of the period, i.e., 2017-2020, we rely on the Main Economic Indicators (MEI) of the Organisation for Economic Co-operation and Development (OECD).[37] We compute the log-returns of real gold prices (r) over the period 1258 to 2020.

We construct a time-series measure of the probability of fatality (pf) from a dataset created by Cirillo and Taleb (2020), who provide start and end dates, lower, average and upper estimates of fatalities, and the population at the time of major pandemics and epidemics from 429 BC, including events with more than 1,000 estimated victims. We use the average estimate of fatalities, and distribute them equally across the years of the event (pandemic or epidemic) to create a time series of fatalities over time. We divide the fatalities by the population estimate at the time of the particular event, which we keep the same if the pandemic or epidemic spans multiple years, to obtain the pf over the period 1258 to 2020, i.e., the same sample size r. Table 6.1 provides complete details of the events considered.

Table 6.1. Details of the Contagious Diseases Considered

Pandemic or Epidemic	Start	End	Average Estimate ($X10^3$)	Population ($X10^6$)
Black Death	1331	1353	137500	392
Sweating Sickness	1485	1551	10	461
Smallpox Epidemic in Mexico	1520	1520	6500	461
Cocoliztli Epidemic of 1545-1548	1545	1548	10000	461
1563 London Plague	1562	1564	20	554
Cocoliztli Epidemic of 1576	1576	1580	2250	554
1592-1593 London Plague	1592	1593	20	554
Malta Plague Epidemic	1592	1593	3	554
Plague in Spain	1596	1602	650	554
New England Epidemic	1616	1620	7	554
Italian Plague of 1629-1631	1629	1631	280	554
Great Plague of Sevilla	1647	1652	150	554
Plague in the Kingdom of Naples	1656	1658	1250	603
Plague in the Netherlands	1663	1664	24	603
Great Plague of London	1665	1666	100	603
Plague in France	1668	1668	40	603
Malta Plague Epidemic	1675	1676	11	603
Great Plague of Vienna	1679	1679	76	603

[36] https://www.bankofengland.co.uk/statistics/research-datasets.
[37] https://www.oecd.org/sdd/oecdmaineconomicindicatorsmei.htm.

Great Northern War Plague Outbreak	1700	1721	192	603
Great Smallpox Epidemic in Iceland	1707	1709	18	603
Great Plague of Marseille	1720	1722	100	603
Great Plague of 1738	1738	1738	50	814
Russian Plague of 1770-1772	1770	1772	50	814
Persian Plague	1772	1772	2000	990
Ottoman Plague Epidemic	1812	1819	300	990
Caragea’s Plague	1813	1813	60	990
Malta Plague Epidemic	1813	1814	5	990
First Cholera Pandemic	1816	1826	100	990
Second Cholera Pandemic	1829	1851	100	990
Typhus Epidemic in Canada	1847	1848	20	990
Third Cholera Pandemic	1852	1860	1000	1263
Cholera Epidemic of Copenhagen	1853	1853	5	1263
Third Plague Pandemic	1855	1960	18500	1263
Smallpox in British Columbia	1862	1863	3	1263
Fourth Cholera Pandemic	1863	1875	600	1263
Fiji Measles Outbreak	1875	1875	40	1263
Yellow Fever	1880	1900	125	1263
Fifth Cholera Pandemic	1881	1896	9	1654
Smallpox in Montreal	1885	1885	3	1654
Russian Flu	1889	1890	1000	1654
Sixth Cholera Pandemic	1899	1923	800	1654
China Plague	1910	1912	40	1654
Encephalitis Lethargica Pandemic	1915	1926	1500	1654
American Polio Epidemic	1916	1916	7	1654
Spanish Flu	1918	1920	58500	2307
HIV/AIDS Pandemic	1920	2020	30000	3712
Poliomyelitis in USA	1946	1946	2	2948
Asian Flu	1957	1958	2000	2948
Hong Kong Flu	1968	1969	1000	3637
London Flu	1972	1973	1	3866
Smallpox Epidemic of India	1974	1974	15	4016
Zimbabwean Cholera Outbreak	2008	2009	4	6788
Swine Flu	2009	2009	364	6788
Haiti Cholera Outbreak	2010	2020	10	7253
Measles in Democratic Republic of Congo (DRC)	2011	2018	5	7253
Ebola in West Africa	2013	2016	11	7176
Indian Swine Flu Outbreak	2015	2015	2	7253
Yemen Cholera Outbreak	2016	2020	4	7643
2018-19 Kivu Ebola Epidemic	2018	2020	2	7643
2019-20 COVID-19 Pandemic	2019	2020	133.5	7643
Measles in DRC	2019	2020	5	7643
Dengue fever	2019	2020	2	7643

Note: Sourced from Table 1 of Cirillo and Taleb (2020).

The variables are plotted in Figure A6.1 in the Appendix to the chapter, while Table A6.1 in the Appendix summarizes the data, and highlights the existence of non-normality of the variables – a preliminary motivation for using a quantiles-based approach to the question in hand.

6.2.2. Methodology

The classical linear predictive mean-regression model is given by:

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{t+1}, i = 1, \dots, N \tag{4}$$

where r_{t+1} is the observed real gold log-returns over time period t to *t+1*, $x_{i,t}$ is a specific predictor at time t, which in our case is the probability of fatality (*pf*), and ε_{t+1} is the error term, which is assumed to be independent with zero mean and variance σ^2. The ordinary least squares (OLS) estimators, $\hat{\alpha}_i, \hat{\beta}_i$, of the parameters in the predictive mean-regression model are estimated by minimizing the quadratic expected loss, $\sum_{t=0}^{T-1}(r_{t+h} - \alpha_i - \beta_i x_{i,t})^2$, with respect to the parameters, α_i, β_i.

The aforementioned model is primarily devised to predict the mean of r_{t+1}, and not the entire conditional distribution of real gold log-returns. Koenker and Bassett (1978) show that quantile regression estimators are more efficient and robust than mean regression estimators in cases where nonlinearities and deviations from normality exist, with both these features existing in our data.

Hence, we consider the predictive quantile regression model of the following form:

$$r_{t+1} = \alpha_i{}^{(\tau)} + \beta_i{}^{(\tau)} x_{i,t} + \varepsilon_{t+1}, i = 1, \dots, N, \tag{5}$$

where $\tau \in (0,1)$, and ε_{t+1} is assumed independent derived from an error distribution $g_\tau(\varepsilon)$ with the τ-th quantile equal to 0. Eq. (2) implies the τ-th quantile of r_{t+1} given $x_{i,t}$, is $Q_\tau(r_{t+1}|x_{i,t}) = \alpha_i{}^{(\tau)} + \beta_i{}^{(\tau)} x_{i,t}$, where the intercept and the coefficients depend on τ. The estimators of the parameters of the predictive quantile regression model in Eq. (2), $\widehat{\alpha_i}^{(\tau)}, \widehat{\beta_i}^{(\tau)}$, are obtained by minimizing the sum $\sum_{t=0}^{T-1} \rho_\tau(r_{t+1} - \alpha_i{}^{(\tau)} - \beta_i{}^{(\tau)} x_{i,t})$, where the so called check function is used, $\rho_\tau(u) = u\big(\tau - I(u < 0)\big) = \frac{1}{2}[|u| + (2\tau - 1)u]$.

6.3. Empirical Findings

6.3.1. Main Results

Though our main focus is the result of the quantiles-based model, we start with the predictive effect of the first lag of *pf* on the conditional mean of real gold returns (*r*) based on the standard OLS regression (with Newey and West (1987) heteroskedasticity and autocorrelation corrected (HAC) standard errors). The corresponding estimate of β_1 in Eq. (4), with the *p*-value in parenthesis, is 53.6788 (0.6379), i.e., we find a positive but statistically insignificant effect. This result tends to suggest that gold can indeed serve as a safe haven, as it is unaffected by the probability of fatality associated with contagious diseases, but cannot be used to hedge such risks, since the increase in real gold returns is not significantly different from zero.

Given the statistically insignificant result of the effect of the probability of fatality due to contagious diseases under the linear model, we check whether this is because of being misspecified. We conduct the Brock et al. (1996) BDS test of nonlinearity, as well as the powerful *UDMax* and *WDMax* tests of multiple structural breaks of Bai and Perron (2003). As shown in Table A6.2 in the Appendix, the null hypothesis of *iid* residuals of Eq. (4) is overwhelmingly rejected across the various dimensions considered and is indicative of uncaptured nonlinearity. As far as regime changes are concerned, we detect five structural breaks, at 1353, 1549, 1649, 1745, and 1920, which correspond to the periods in and around Black Death, Sweating Sickness and Cocoliztli Epidemic of 1545-1548, Great Plague of Sevilla, Great Plague of 1738, Spanish Flu and HIV/AIDS pandemic. Over and above the non-normal distributions of the variables, these results from the nonlinearity and structural instability analyses highlight, on the one hand, the inappropriateness of the linear predictive regression model and, on the other, the necessity of employing a quantiles-based approach.

Given the issue of misspecification of the linear model, we turn to the effect of the lagged *pf* on real gold returns, i.e., *r*, under the quantile regression approach reported in Figure 6.1. We find that *pf* tends to negatively predict *r* over the quantile range 0.10 to 0.40, though the effect is only statistically significant at the 5% level at τ=0.15 (and at the 10% level for τ=0.10 and 0.20). The predictive impact of *pf* on the conditional distribution *r* turns positive over τ=0.45 to 0.90, but the effect is statistically significant at the 5% level only beyond the median, i.e., τ=0.55 to 0.90. In summary, our findings suggest that gold cannot serve as a hedge against the fatality risks emanating from contagious diseases in its bearish phase, but turns into a safe haven just around the normal state of the market i.e., the median, and a hedge beyond it.[38] Alternatively put, evidence in favour of gold serving as a hedge against rare disaster risks, involving the probability of death due to contagious diseases, exists when gold returns tend to be generally high, i.e., beyond the median and into its bullish phase.[39]

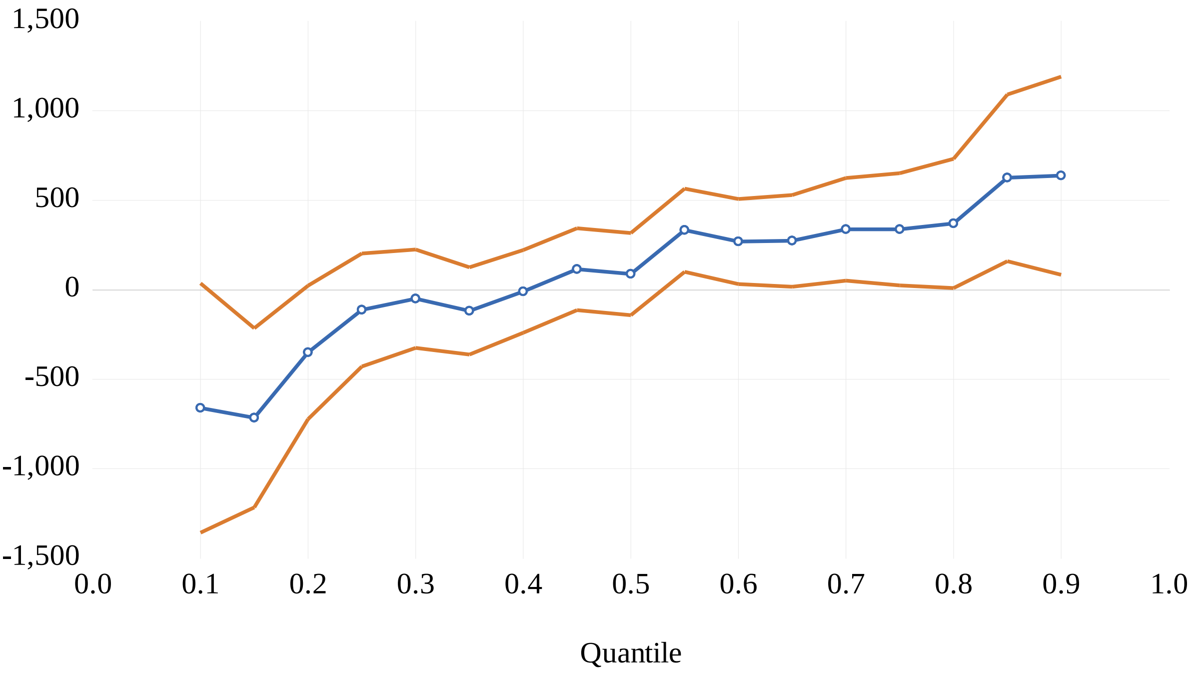


Figure 6.1. Slope parameter estimate from quantile regression: real gold returns (*r*) on lagged probability of fatality (*pf*) due to contagious diseases.

Note: The figure plots the slope estimates 18 equally spaced quantiles from the 0.10-th quantile to 0.90-th quantile (blue-line with circles). A point-wise 95% confidence interval is indicated (brown line) around the quantile regression parameter estimates.

6.3.2. Additional Results

For further analysis, we firstly use the quantile-on-quantile regression approach of Sim and Zhou (2015), to investigate whether the quantile (τ)-specific impact on real gold returns is dependent on the size of the probability of fatality, i.e., its quantiles (θ). As can be seen from Figure A6.2 in the Appendix to the chapter, the size of the lagged probability of fatality does not tend to alter the results obtained from the quantile regression. That is, the hedging strength

[38] Comparatively, using real silver returns over the period 1688 to 2020, with the underlying data derived from the same sources, we find that lagged *pf* negatively and significantly impacts real silver returns over the quantile range of 0.15-0.30, and insignificantly beyond it to 0.90. This finding, complete details of which are available upon request from the authors, shows that silver cannot act as a hedge against the risks associated with deaths due to contagious diseases.

[39] A similar observation related to cases and deaths associated with COVID-19 is made by Wang (2021), who also relies on a quantiles-based approach.

of gold at its upper conditional quantiles is unaffected by the magnitude of the probability of death due to contagious diseases. This is possibly an indication that, once the world witnesses such rare disaster risks, the size of the associated probability of fatality does not necessarily change the behaviour of gold returns. Secondly, given that the literature discussed in the introduction suggests that fatalities associated with COVID-19, which is a rare disaster, can lead to increases in macroeconomic uncertainty, it is likely that *pf* can also predict the volatility of gold returns. Given this, we obtain the conditional volatility of real gold returns (*vr*) by fitting a standard generalized autoregressive conditional heteroskedasticity (GARCH) model, then regress it on lagged *pf* using the quantile regression model specified in Eq. (2). The findings are plotted in Figure A6.3 in the Appendix to the chapter, which shows a positive impact of lagged *pf* over the entire conditional distribution of *vr*.[40] On one hand, the positive impact on volatility at the lower quantiles of *vr* can be associated with the well-known leverage effect in the gold market (Asai et al., 2020), whereby the negative effect on gold returns in its bearish state due to *pf* enhances volatility. On the other hand, higher gold returns during its bullish phase resulting from increased *pf* possibly drives up *vr* due to higher trading in the gold market (Bouri et al., 2021).

6.4. Conclusion

In this chapter, we analyse the predictive effect of the probability of fatality due to 62 outbreaks of contagious diseases on real gold returns over the period 1258 to 2020, based on a quantile regression approach. While standard linear (conditional mean) predictive regression fails to show any significant effect of the rare disaster risks variable, i.e., probability of fatality due to contagious diseases, on real gold returns, the quantile regression method gives evidence of a significant negative impact at lower conditional quantiles, and a significant positive effect at upper conditional quantiles. Due to the existence of non-normality, nonlinearity and structural breaks in our data and the predictive relationship of the two variables of concern, the quantile regression result should be considered more reliable than the linear predictive model. Our findings tend to suggest that gold serves as a hedge during its bullish state against associated risks of the probability of death due to outbreaks of contagious diseases.

Our findings have important implications for investors. Understandably, in the wake of outbreaks of contagious diseases, gold market players must be aware that the safe haven

[40] The conditional mean estimate of the lagged effect of *pf* on *vr* is 2394.0780, with a *p*-value of 0.0821.

property of gold is only likely to hold if the market is already performing well since only then can gold hedge against such risks via increased real returns. However, for this information to be available to investors, they must be aware that one needs to rely on an underlying quantiles-based econometric model.

As far as future research is concerned, it would be interesting to extend our in-sample predictive analyses to an out-of-sample forecasting analysis involving both gold returns and volatility.

Chapter 7

General Conclusion

Given the high levels of uncertainty from the outbreak of the COVID-19 pandemic, we go beyond the previous literature on forecasting the realised volatility of the returns of the US Treasury securities, international stocks, foreign exchange rate, Bitcoin, agricultural commodities and gold futures. The novel direction of this study is on exploring the predictive power of uncertainty-associated contagious diseases, especially, the Covid-19 pandemic, as it is considered as a rare disaster.

Employing the heterogeneous autoregressive realised variance (HAR RV) model, in chapter 2, we investigate the forecasting ability of daily infectious diseases-related uncertainty (EMVID on the US Treasury securities. Our recursive out-of-sample results provide evidence that the EMVID index plays an important role in predicting the future path of the US Treasury securities considering the entire sample period under investigation. Notable, the EMVID index can explain the volatility of the US Treasury securities when evaluated within the COVID-19 episode. Also, our findings serve as a reminder of the important role government securities play as a benchmark interest rates, hedging interest rate risk and liquidity management. These findings have important policy implications for investors and portfolio managers when faced with infectious diseases-related uncertainty.

Chapter 3 looks at the predictive power of the EMVID index on international stock futures. The HAR-RV out-of-sample model provides evidence that the EMVID index has predictive power for the realised volatility of the international stock futures given the whole sample period. For robustness check, we examine the role of the EMVID index within the COVID-19 period. Through the use of the MSE-F test, it was statistically evident that the EMVID index plays an important role in predicting the future path of the international stock future. However, the most vulnerable stock markets to EMVID are Singapore, Portugal and the Netherlands. Nevertheless, our findings provide evidence that stock markets are crucially linked to the economy through improving liquidity, capital mobilisation, risk pooling management, and enhancing managers' and corporates' control. Most important, these findings suggest that investors seeking opportunities for international stocks diversification in the short and long forecast amid contagious diseases need to take our finding into consideration when making policies.

In chapter 4, we explore the predictability of the foreign exchange rate and Bitcoin futures amid uncertainty from contagious diseases. Our out-of-sample HAR-RV model results indicate that the EMVID index plays a crucial role in forecasting the volatility of the foreign exchange and Bitcoin futures. In particular, the Bitcoin futures had the highest significant forecast gain in the whole sample period and the same was evident when we extended our analysis within the COVID-19 range. Our results contribute to the existing literature by showing the ability of the EMVID index is predict the future path of the major foreign exchange rate and Bitcoin given uncertainties from infectious diseases. Also, it emphasises the disconnection of Bitcoin from any economic fundamentals and governments. Contemporary, an efficient foreign exchange rate and cryptocurrency market through the use of relevant hedging instruments in important for the performance of our economies. These findings have important implications for investors, traders and speculators in the foreign exchange rate and cryptocurrency markets when uncertainty from contagious diseases arise.

Looking at the predictability of agricultural commodities “the softs” given the daily infectious diseases-related uncertainty in chapter 5. Our recursive out-of-sample results depict the important role the EMVID index plays in predicting the future path of agricultural commodity traded futures. These results were statistically significant only within the COVID-19 episode, suggesting that the EMVID index and in particular the restriction of movement between countries can explain the volatility of this asset class. We contribute to previous literature by highlighting the important role played by EMVID in the agricultural sector’s commodity traded futures when exposed to food supply chain disruption from lockdown given contagious disease outbreaks.

Furthermore, in chapter 6, we use the quantile regression model over annual data from 1258 to 2020 to detect nonlinearity and regime changes in the relationship between real gold returns and the probability of fatality due to contagious diseases. Our results show that real gold returns can hedge against the risks associated with contagious diseases, especially when the market is in its bullish state, with it being negatively impacted in its bearish state. Also the volatility in the gold market could be detrimental to economic growth of resource-producing economies (Guan et al. 2021). Therefore, mitigating this impact is crucial for our economies. We contribute to the existing literature on real gold returns by highlighting its importance for investors seeking refuge in the safe haven of gold during rare disaster events.

Future contracts are inherently forward-looking and embed investor expectations of the future macroeconomic environment. Therefore, our results provide evidence on the positive future perspective investors have on the global economy. In conclusion, we contribute to the existing literature by providing findings that emphasise the importance of accurate volatility forecasts in the US Treasury securities, international stocks, the foreign exchange rate, Bitcoin, agricultural commodities and gold futures to enhance the computations of options investment position, strategic assets allocation and pricing of derivatives when investor and portfolio managers are faced with uncertainty related to contagious diseases. In the future we will extend our study on the predictability of sectoral and local financial assets realised volatility in their respective categories.

APPENDIX

Table A2.1. Summary Statistics.

	CGB		ED		FV		TU		TY		US	
Statistic	**RV**	**EMVID**	**RV**	**EMVID**	**RV**	**EMVID**	**RV**	**EMVID**	**RV**	**EMVID**	**RV**	**EMVID**
Mean	0.044531	1.305998	0.480685	3.779621	0.025944	2.360124	0.007351	2.542798	0.044354	2.488738	0.090268	2.512092
Median	0.041109	0.000000	0.342320	0.310000	0.023405	0.000000	0.006269	0.270000	0.040070	0.000000	0.081920	0.275000
Maximum	0.295151	77.35000	3.000000	77.35000	0.113880	77.35000	0.046177	77.35000	0.195469	77.35000	0.481995	77.35000
Minimum	2.97E-05	0.000000	0.001708	0.000000	0.006628	0.000000	4.24E-05	0.000000	0.012231	0.000000	0.026771	0.000000
Std. Dev.	0.020923	4.888319	0.453826	9.000485	0.011592	7.035670	0.004917	7.448375	0.018765	7.377947	0.038852	7.426129
Skewness	2.097236	6.843236	2.800155	3.197233	1.968654	4.397566	2.369175	4.308086	2.488910	4.389310	3.664693	4.364571
Kurtosis	15.25013	61.59007	13.58228	15.02220	10.39266	26.40966	12.54743	25.40030	14.51353	26.28666	28.61855	25.95301
Jarque-Bera	39050.65	843185.2	7728.853	9997.363	6576.916	58628.12	10693.11	54217.13	14757.18	58088.25	66032.79	56082.58
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	5590	5590	1294	1294	2250	2250	2259	2259	2251	2251	2232	2232

Notes: Table A2.1 represent the summary statistics of variables Realised Volatility (RV) and the newspaper-based uncertainty index because of infectious diseases (EMVID). CGB: Canadian 10 Year Futures, ED: Eurodollar Futures CME, FV: US 5-Year T-Note Futures, TU: US 2-Year T-Note Futures, TY: US 10-Year T-Note Futures and US: US 30-Year T-Bond Futures Std. Dev. is the standard deviation and p-value is the null hypothesis of normality associated with the Jarque-Bera test.

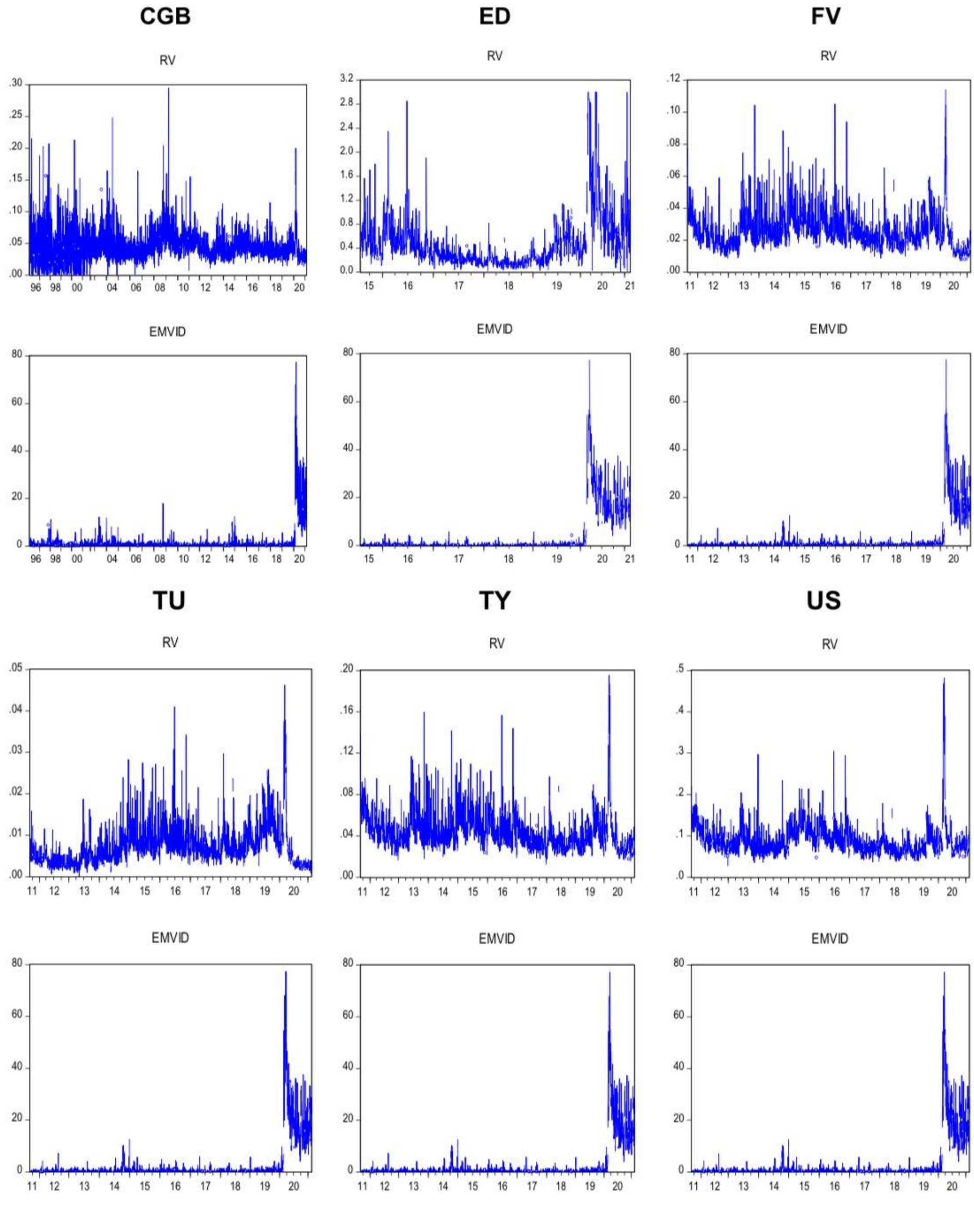


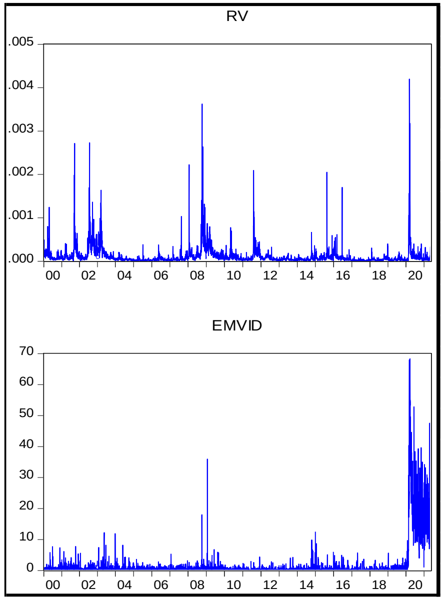
Figure A2.1. Data Plots

Notes: RV is the daily realised volatility variance estimation for the US 30-Year T-Note futures; EMVID is that daily newspaper-based uncertainty index due to infectious diseases. CGB: Canadian 10 Year Futures, ED: Eurodollar Futures CME, FV: US 5-Year T-Note Futures, TU: US 2-Year T-Note Futures, TY: US 10-Year T-Note Futures and US: US 30-Year T-Bond Futures

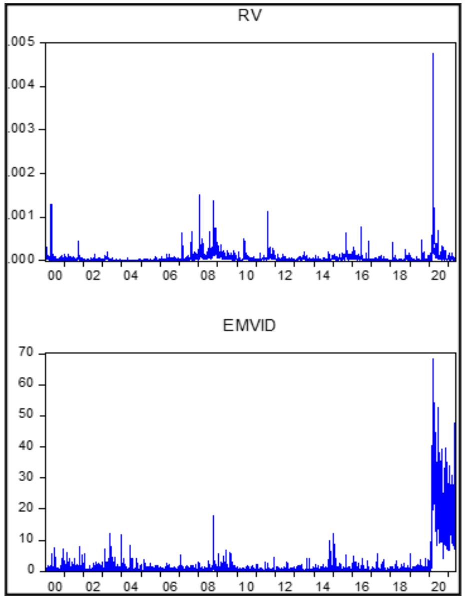
Table A3.1. Acronyms of Each Stock Markets Index

Symbol	Name	City, Country
	Europe	
1. AEX	Amsterdam Exchange index	Amsterdam, Netherlands
2. BFX	Bell 20 Index	Brussel, Belgium
3. BVLG	PSI All-Share Index	Lisbon, Portugal
4. FCHI	CAC 40	Paris, France
5. FTMIB	FTSE MIB	Milan, Italia
6. FTSE	FTSE 100	London, United Kingdom
7. GDAXI	DAX	Frankfurt, Germany
8. IBEX	IBEX 35 Index	Madrid, Spain
9. OMXC20	OMX Copenhagen 20 Index	Copenhagen, Denmark
10. OMXHPI	OMX Helsinki All Share Index	Helsinki, France
11. OMXSPI	OMX Stockholm All Share Index	Stockholm, Sweden
12. OSEAX	Oslo Exchange All-share Index	Oslo, Norway
13. SMSI	Madrid General Index	Madrid, Spain
14. SSMI	Swiss Stock Market Index	Zurich, Switzerland
15. STOXX50E	EURO STOXX 50	Eschborn, Germany
	Asia	
16. BSESN	S&P BSE Sensex	Bombay, India
17. HSI	HANG SENG Index	Hong Kong, China
18. KS11	Korea Composite Stock Price Index (KOSPI)	Seaul, South Korea
19. KSE	Karachi SE 100 Index	Karachi, Paristan
20. N225	Nikkei 225	Tokyo, Japan
21. NSEI	NIFTY 50	Mumbai, Maharashtra, India
22. SSEC	Shanghai Composite Index	Shanghai, China
23. STI	Straits Times Index	Shenton Way, Singapore
	North America	
24. DJI	Dow Jones Industrial Average	New York, United State
25. GSPTSE	S&P/TSX Composite index	Toronto, Canada
26. IXIC	Nasdaq 100	New York, United State
27. MXX	IPC Mexico	Mexico City, Mexico
28. RUT	Russel 2000	New York, United State
29. SPX	S&P 500 Index	New York, United State
	South America	
30. BVSP	BVSP BOVESPA Index	Rio de Janeiro, Brazil
	Australia	
31. AORD	All Ordinaries	Sydney, Australia

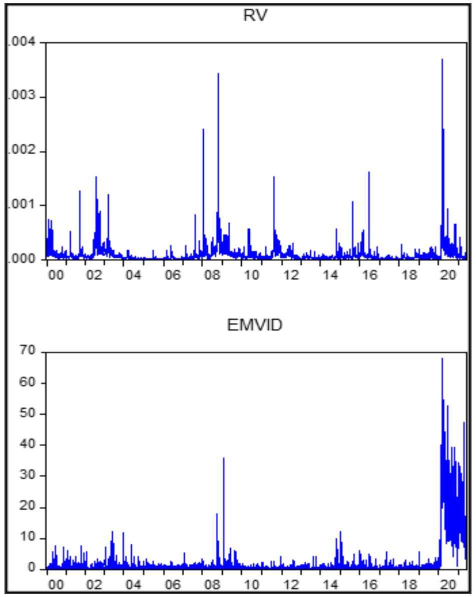
AEX



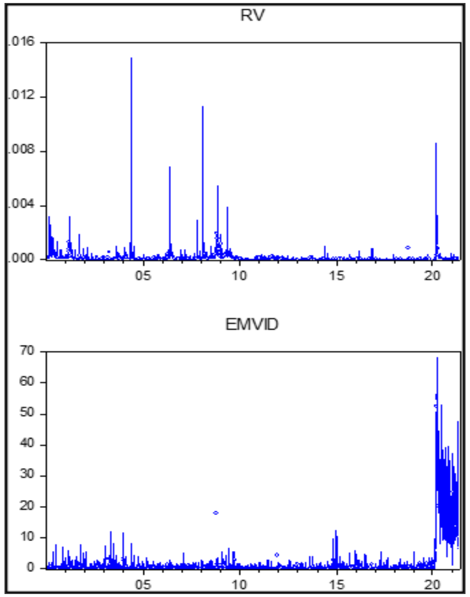
AOR



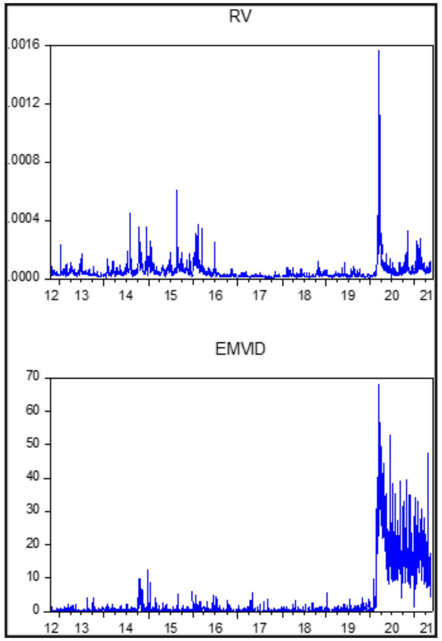
BFX



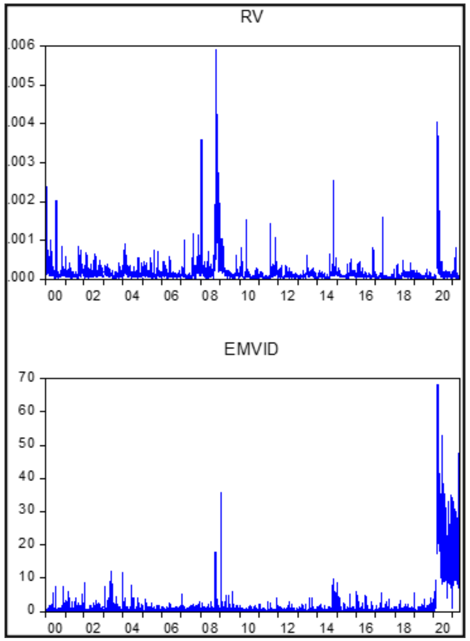
BSES



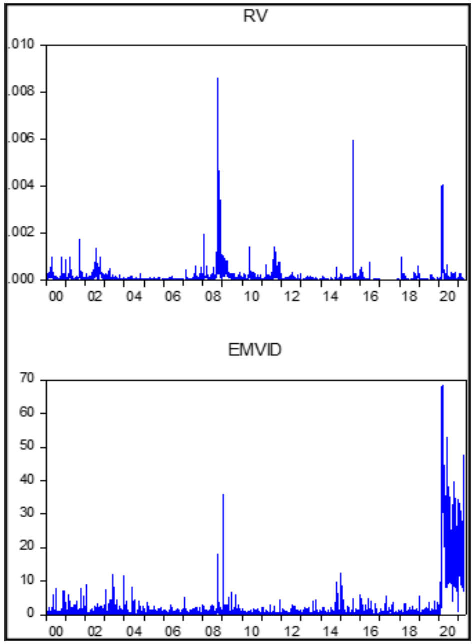
BVL



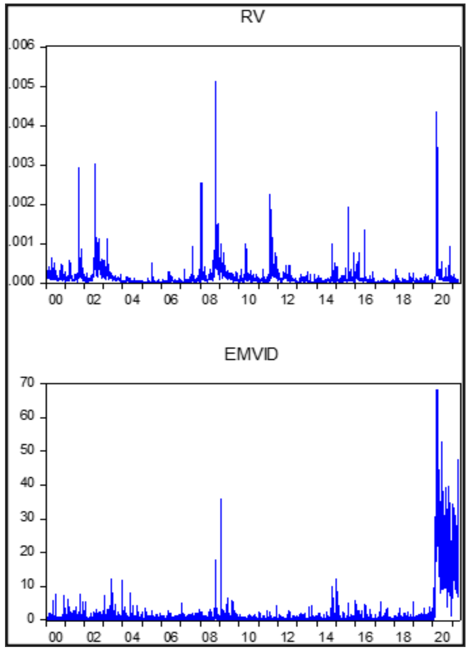
BVSP



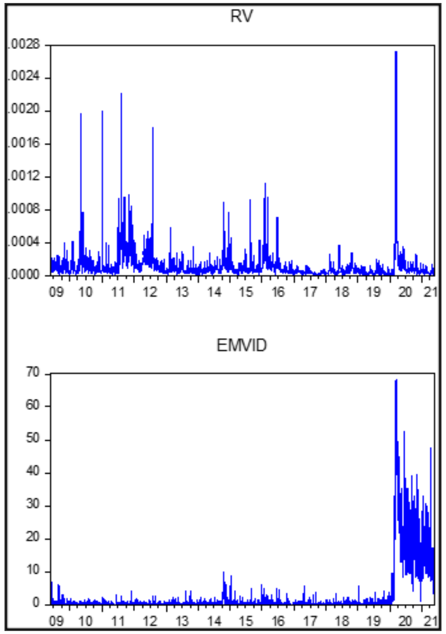
DJI



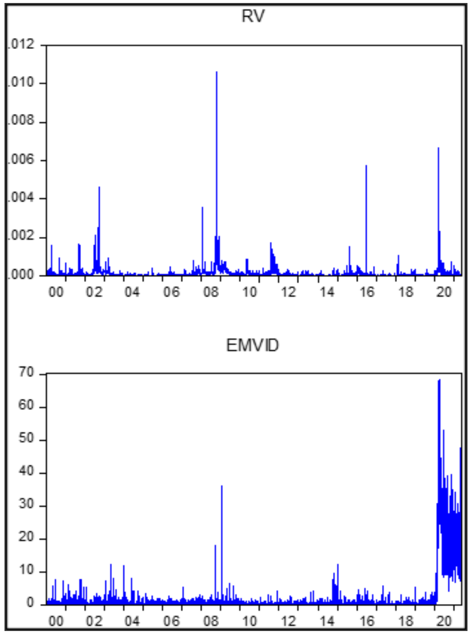
FCHI



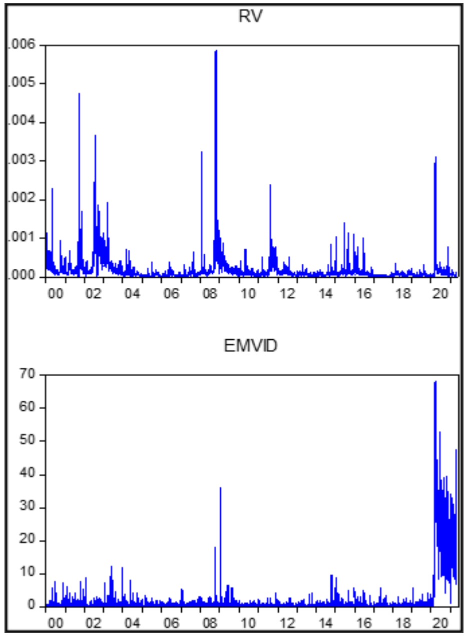
FTMIB



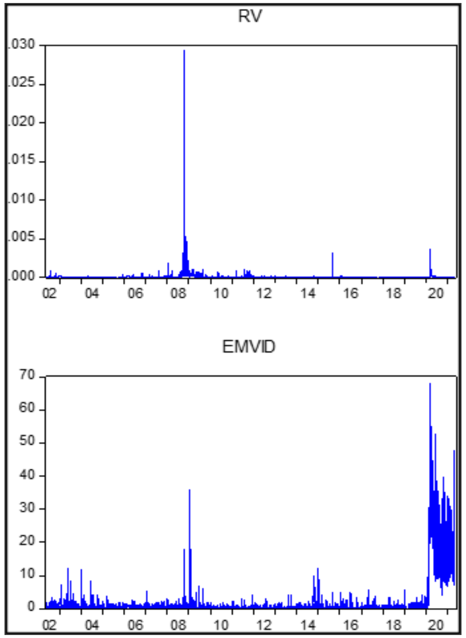
FTSE



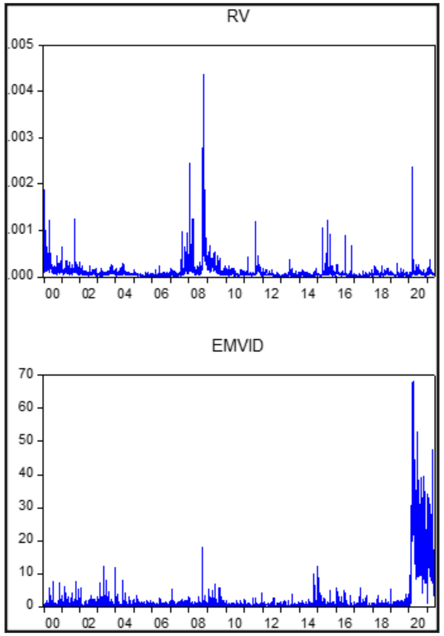
GDAXI



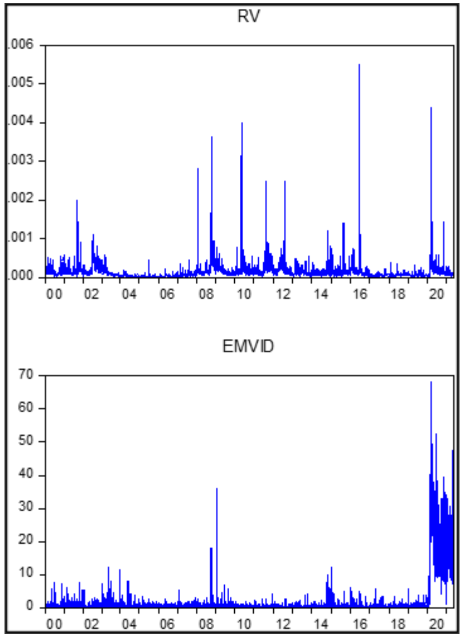
GSPTSE



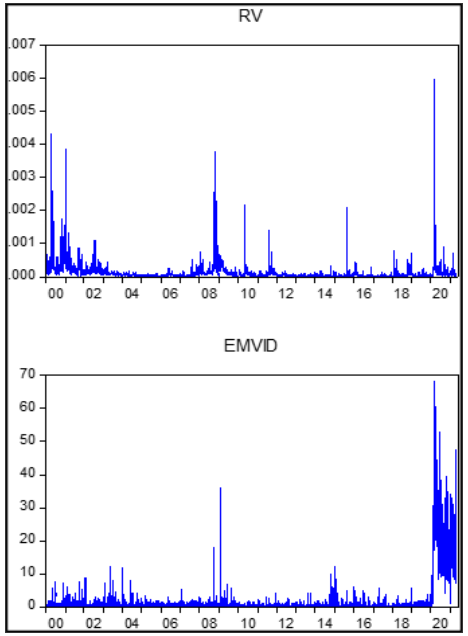
HSI



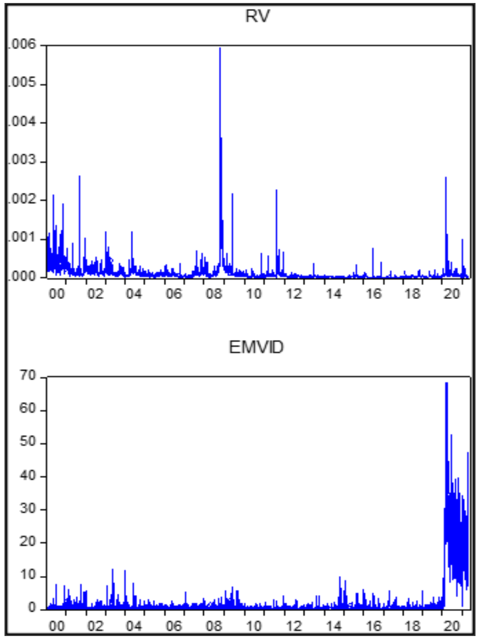
IBE



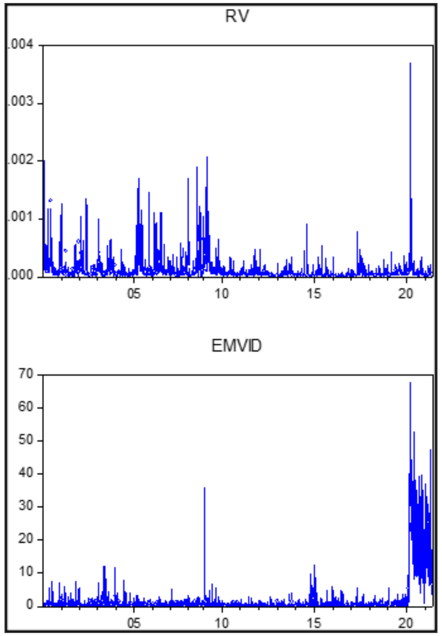
IXI



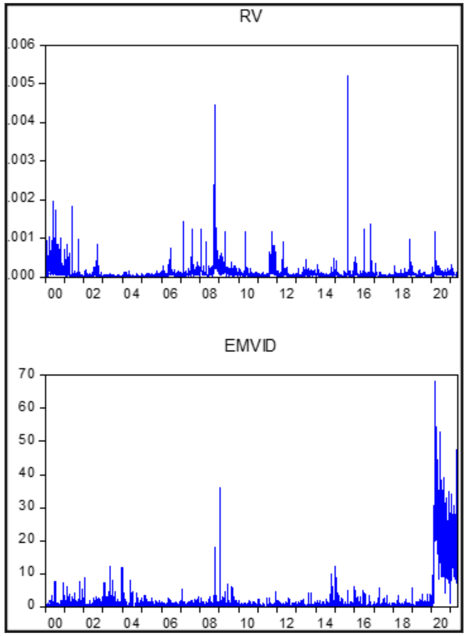
KS11



KSE



MX



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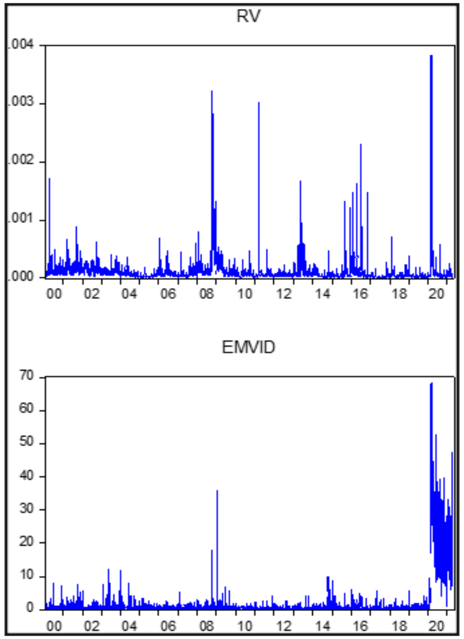
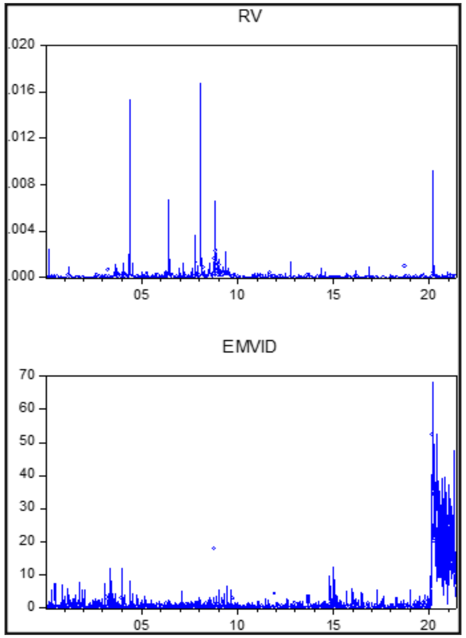


NSEI



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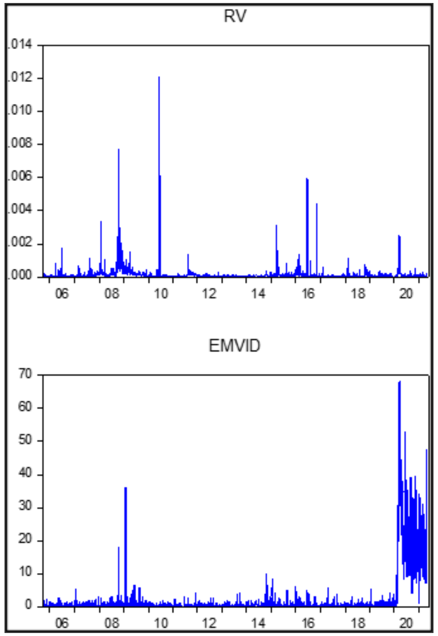
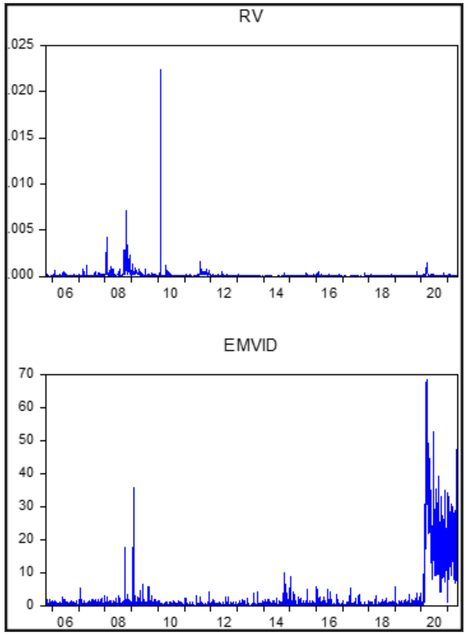
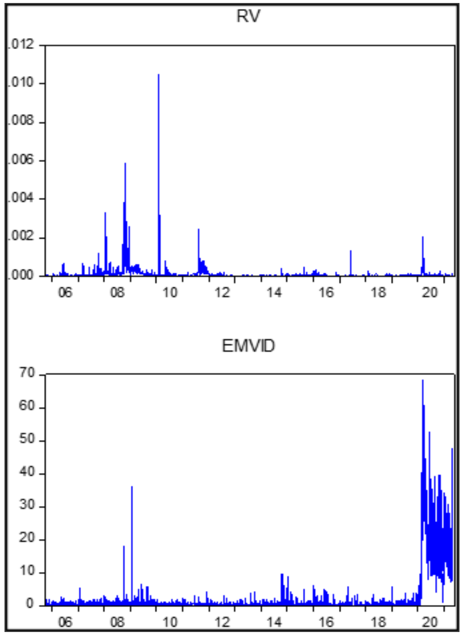


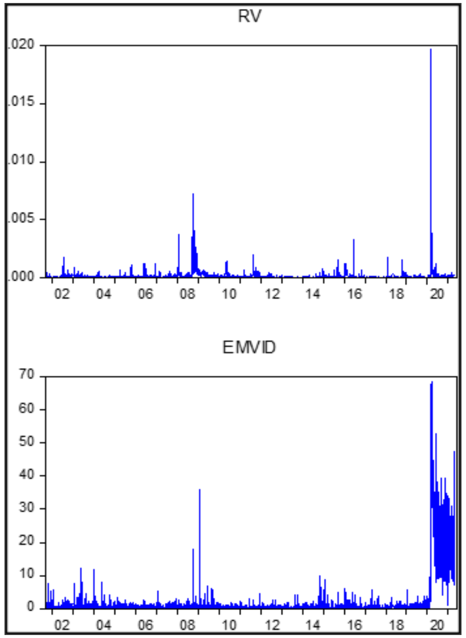
OMXHPI



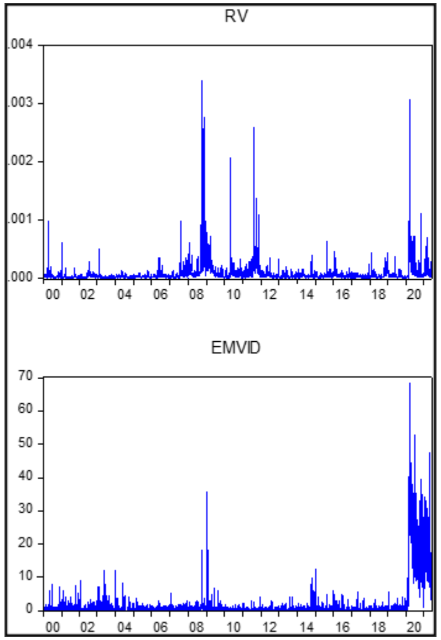
OMXSPI



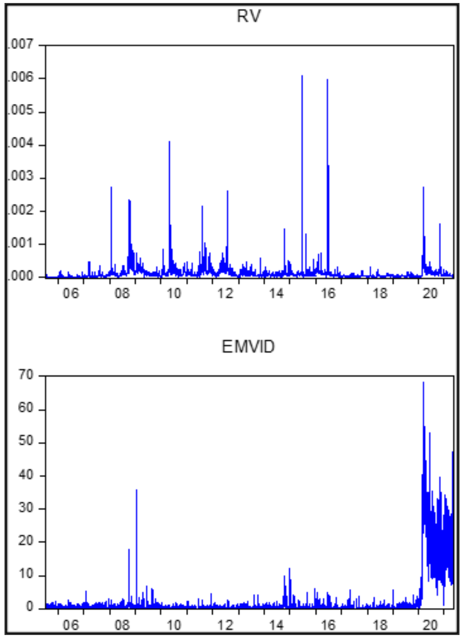
OSEA



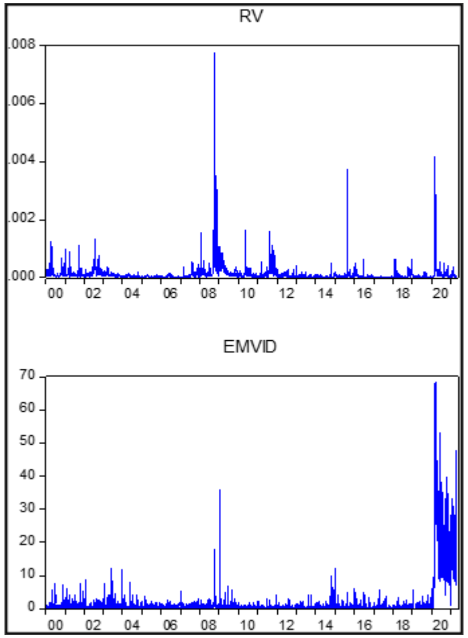
RUT



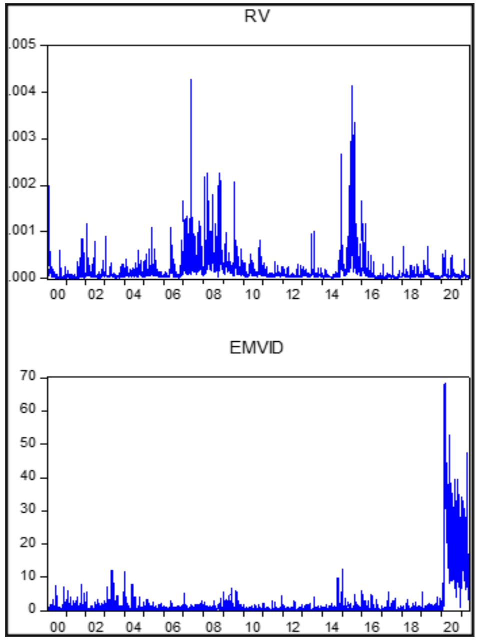
SMSI



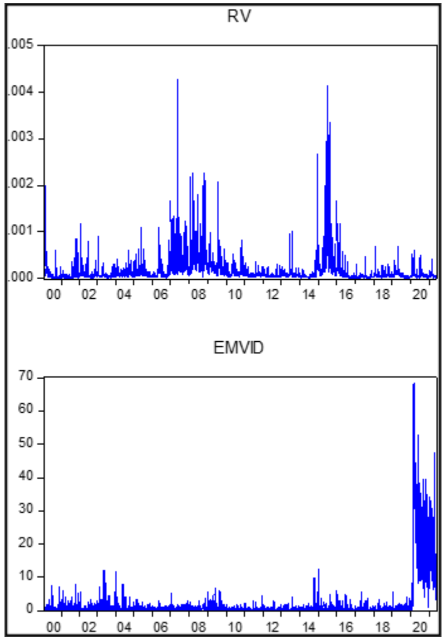
SPX



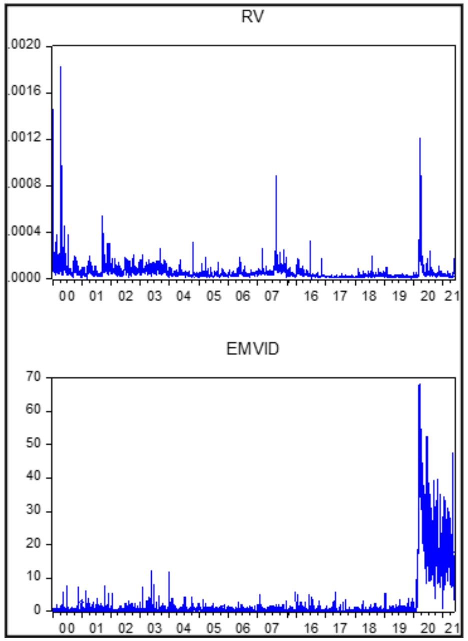
SSEC



SSM



ST



STOXX50

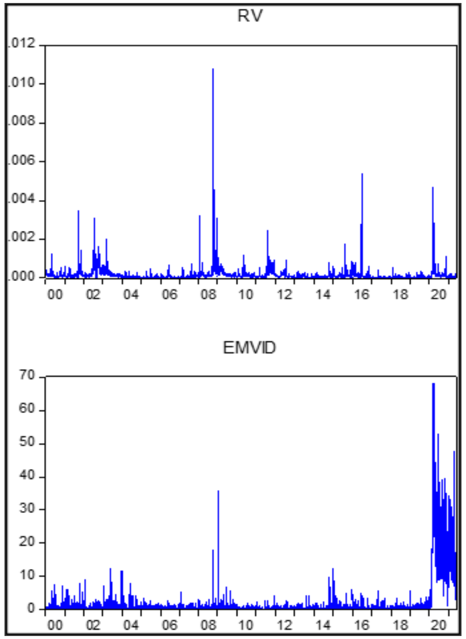


Figure A3.1. Data Plots. **Note:** RV is the realised volatility estimates for international stock markets index: EMVID the newspaper-based uncertainty index due to infectious diseases. * indicates stock markets shocks because of infectious diseases.

Table A3.2. Out-of-Sample Forecasting Gains for the COVID-19 Episode

Horizon	RMSFE$_0$	RMSFE $_1$	FGs	RMSFE$_0$	RMSFE $_1$	FGs
			Europe			
	Panel 1: AEX: 3/16/2020			Panel 2: BFX: 3/16/2020		
h=1	1.9360	1.9505	−0.7438	2.1234	2.1210	0.1135
h=5	0.6168	0.6193	−0.4034	0.5541	0.5545	−0.0853
h=22	0.1865	0.1867	−0.0691	0.1618	0.1615	0.2155
	Panel 3: BVLG: 3/18/2020			Panel 4: FCHI: 3/16/2020		
h=1	0.6593	0.6572	0.3162	2.4805	2.4790	0.0597
h=5	0.1838	0.1839	−0.0625	0.6902	0.6899	0.0406
h=22	0.0660	0.0654	0.9168	0.1916	0.1913	0.1490
	Panel 5: FTMIB: 3/16/2020			Panel 6: FTSE: 3/16/2020		
h=1	1.0847	1.0839	0.0824	1.7204	1.7216	−0.0692
h=5	0.3324	0.3326	−0.0532	0.6743	0.6712	0.4635
h=22	2.4875	2.4842	0.1301	0.2173	0.2168	0.2048
	Panel 7: GDAX1: 3/16/2020			Panel 8: IBEX: 3/18/2020		
h=1	1.6569	1.6574	−0.0350	1.6970	1.6990	−0.1178
h=5	0.4315	0.4322	−0.1485	0.5262	0.5269	−0.1329
h=22	0.1357	0.1355	0.2045	0.1713	0.1713	0.0012
	Panel 9: OMXC20: 3/18/2020			Panel 10: OMXHPI: 3/16/2020		
h=1	1.1987	1.1988	−0.0105	0.8285	0.8291	−0.0776
h=5	0.2935	0.2939	−0.1337	0.2196	0.2200	−0.2041
h=22	0.1009	0.1008	0.1478	0.0706	0.0703	0.5281
	Panel 11: OMXSPI: 3/17/2020			Panel 12: OSEAX: 3/11/2020		
h=1	0.8960	0.8957	0.0394	2.6408	2.7287	−3.2222
h=5	0.2071	0.2071	−0.0092	2.0396	2.0436	−0.1945
h=22	0.0814	0.0811	0.2996	0.5292	0.5297	−0.0831
	Panel 13: SMSI: 3/16/2020			Panel 14: SSMI: 3/17/2020		
h=1	1.4601	1.4571	0.2040	1.8434	1.8452	−0.0942
h=5	0.3939	0.3938	0.0422	0.5770	0.5786	−0.2798
h=22	0.1312	0.1310	0.1557	0.2138	0.2129	0.4335
	Panel 15: STOXX50E: 3/16/2020					
h=1	2.1622	2.1663	−0.1882			
h=5	0.5424	0.5441	−0.3121			
h=22	0.2152	0.2141	0.5133			
			Asia			
	Panel 16: BSESN: 6/16/2004			Panel 17: HIS: 3/17/2020		
h=1	1.5849	1.6314	−2.8460	0.5010	0.5184	−3.3552
h=5	0.9199	0.9189	0.1121	0.2843	0.2839	0.1406
h=22	0.2426	0.2427	−0.0387	0.0665	0.0668	−0.4584
	Panel 18: KS11: 3/17/2020			Panel 19: KSE: 3/16/2020		
h=1	1.4359	1.4280	0.5490	2.2063	2.1875	0.8595
h=5	0.4078	0.4017	1.5029	0.6173	0.6116	0.9344
h=22	0.1037	0.1035	0.1082	0.1541	0.1539	0.1410
	Panel 20: N225: 3/18/2020			Panel 21: NSEI: 3/17/2020		
h=1	0.8578	0.8597	−0.2159	1.6255	1.6764	−3.0350
h=5	0.3704	0.3722	−0.4707	0.9785	0.9769	0.1570
h=22	0.1205	0.1207	−0.1459	0.2558	0.2564	−0.2297
	Panel 22: SSEC: 3/18/2020			Panel 23: STI: 3/16/2020		
h=1	0.5192	0.5222	−0.5686	0.5072	0.5045	0.5404

h=5	0.1389	0.1394	−0.3243	0.1697	0.1688	0.5718
h=22	0.0400	0.0400	−0.0350	0.0456	0.0456	0.0153
North America						
	Panel 24: DJI: 3/16/2020			Panel 25: GSPTSE: 3/17/2020		
h=1	1.8333	1.8403	−0.3792	0.6681	0.6831	−2.1965
h=5	0.4916	0.4932	−0.3256	0.3700	0.3716	−0.4322
h=22	0.1832	0.1826	0.3675	0.1108	0.1105	0.3033
	Panel 26: IXIC: 3/18/2020			Panel 27: MXX: 3/18/2020		
h=1	1.3779	1.3990	−1.5101	0.5697	0.5700	−0.0575
h=5	0.5258	0.5279	−0.4052	0.1697	0.1697	−0.0471
h=22	0.1631	0.1626	0.3014	0.0441	0.0442	−0.2601
	Panel 28: RUT: 3/17/2020			Panel 29: SPX: 3/16/2020		
h=1	1.8075	1.8110	−0.1880	1.8732	1.8788	−0.2985
h=5	0.5059	0.5058	0.0263	0.5181	0.5190	−0.1746
h=22	0.1644	0.1627	1.0222 ***	0.1824	0.1820	0.2539
South America				Australia		
	Panel30: BVSP: 3/10/2020			Panel 31: AORD: 3/17/2020		
h=1	2.3643	2.3499	0.6146	2.6429	2.6307	0.4641
h=5	0.6400	0.6367	0.5303	0.6724	0.6694	0.4553
h=22	0.2010	0.2011	−0.0055	0.2126	0.2126	0.0075

Note: AEX: Amsterdam Exchange index, BFX: Bell 20 Index, BVLG: Portugal Stock Index (PSI) All-Share Index, FCHI: Cotation Assistée en Continu (CAC) 40, FTMIB: Financial Times Stock Exchange (FTSE), Milano Indice di Borsa (MIB), FTSE: FTSE 100, GDAXI: Deutscher Aktienindex (DAX), IBEX: IBEX 35 Index, OMXC20: OMX Copenhagen 20 Index, OMXHPI: OMX Helsinki All Share Index, OMXSPI: OMX Stockholm All Share Index, OSEAX: Oslo Exchange All-share Index, SMSI: Madrid General Index, SSMI: Swiss Stock Market Index, STOXX50E: EURO STOXX 50 , BSESN: S&P BSE Sensex, HIS: HANG SENG Index, KS11: Korea Composite Stock Price Index (KOSPI), KSE: Karachi SE 100 Index, N225: Nikkei 225, NSEI: NIFTY 50, SSEC: Shanghai Composite Index, STI: Straits Times Index, DJI: Dow Jones Industrial Average, GSPTSE: S&P/TSX Composite index, IXIC: Nasdaq 100, MXX: IPC Mexico, RUT: Russel 2000, SPX: S&P 500 Index, BVSP: BVSP BOVESPA Index, and AORD: All Ordinaries. Within the COVID-19 episode, the forecasting gains, $FG = \left(\frac{RMSFE_0}{RMSFE_1} - 1\right) * 100$. where $RMSFE_0$ and $RMSFE_1$ are root mean squared forecast errors ($RMSFE_s$) of the benchmark HAR-RV model and the extended HAR-RV model. RV is the daily realised volatility estimation of the international stock market index; EMVID is the newspaper-based uncertainty index due to infectious diseases. *** indicates significance at a 1% level.

Table A3.3. Acronyms of Each Implied Volatility Index.

EUROPE	
VSTOXX VOLATILITY INDEX	EU
VDAX-NEW VOLATILITY INDEX	GERMANY
VSMI VOLATILITY INDEX	SWISS
ASIA	
HSI VOLATILITY INDEX	HONG KONG
INDIA VOLATILITY INDEX	INDIA
VKOSPI VOLATILITY INDEX	KOREA
CBOE CHINA ETF VOLATILITY INDEX	CHINA
NIKKEI STOCK AVERAGE VOLATILITY INDEX	JAPAN
NORTH AMERICA	
CBOE SPX VOLATILITY VIX (NEW)	USA
S&P/TSX COMPOSITE LOW VOLATILITY	CANADA

AUSTRILIA	
S&P/ASX 200 VOLATILITY INDEX	AUSTRILIA
SOUTH AMERICA	
CBOE BRAZIL ETF VOLATILITY INDEX	BRAZIL
AFRICA	
SOUTH AFRICA VOLATILITY INDEX	SOUTH AFRICA

Table A3.4. Out-of-Sample Forecasting Gains for the COVID-19 Episode.

EUROPE			
	$RMSFE_0$	$RMSFE_1$	FGs
Panel 1: VSTOXX VOLATILITY INDEX			
h = 1	1.7999	1.6686	7.8705
h = 5	0.4366	0.4293	1.7119
h = 22	0.1735	0.1330	30.4683
Panel 2: VDAX-NEW VOLATILITY INDEX			
h = 1	2.9079	2.0593	41.2069
h = 5	0.5717	0.5126	11.5170
h = 22	0.2712	0.2159	25.6034
Panel 3: VSMI VOLATILITY INDEX			
h = 1	2.0768	1.6741	24.0544
h = 5	0.4200	0.4204	−0.1066
h = 22	0.2076	0.1870	11.0462
ASIA			
Panel 4: HSI VOLATILITY INDEX			
h = 1	1.8673	1.8127	3.0174
h = 5	0.4847	0.4517	7.2982
h = 22	0.1889	0.1673	12.8981
Panel 5: INDIA VOLATILITY INDEX			
h = 1	1.5582	1.5562	0.1331
h = 5	0.4077	0.3992	2.1224
h = 22	0.1879	0.1879	−0.0218
Panel 6: VKOSPI VOLATILITY INDEX			
h = 1	2.2884	1.8664	22.6129
h = 5	0.6329	0.4665	35.6702
h = 22	0.1999	0.1858	7.5766
Panel 7: CBOE CHINA ETF VOLATILITY INDEX			
h = 1	2.7090	2.7104	−0.0524
h = 5	0.8047	0.7594	5.9612
h = 22	0.2272	0.2105	7.9264
Panel 8: NIKKEI STOCK AVERAGE VOLATILITY INDEX			
h = 1	1.8115	1.7283	4.8149
h = 5	0.4289	0.4025	6.5451
h = 22	0.2105	0.1588	32.5444
NORTH AMERICA			
Panel 9: CBOE SPX VOLATILITY VIX (NEW)			
h = 1	2.4810	2.4959	−0.5952
h = 5	0.6034	0.6030	0.0721

h = 22	0.2605	0.2270	14.7473
Panel 10: S&P/TSX COMPOSITE LOW VOLATILITY			
h = 1	4.8002	4.6895	2.3597
h = 5	1.2127	1.1976	1.2536
h = 22	0.4849	0.4843	0.1334
AUSTRALIA			
Panel 11: S&P/ASX 200 VOLATILITY INDEX			
h = 1	1.7999	1.6686	7.8705
h = 5	0.4366	0.4293	1.7119
h = 22	0.1735	0.1330	30.4683
SOUTH AMERICA			
Panel 12: CBOE BRAZIL ETF VOLATILITY INDEX			
h = 1	3.3812	3.3574	0.7070
h = 5	0.8698	0.8543	1.8186
h = 22	0.3665	0.3673	−0.2164
AFRICA			
Panel 13: SOUTH AFRICA VOLATILITY INDEX			
h = 1	1.1539	1.1568	−0.2519
h = 5	0.2886	0.2876	0.3320
h = 22	0.1140	0.1149	−0.7554

Note: See Notes to Table A3.2.

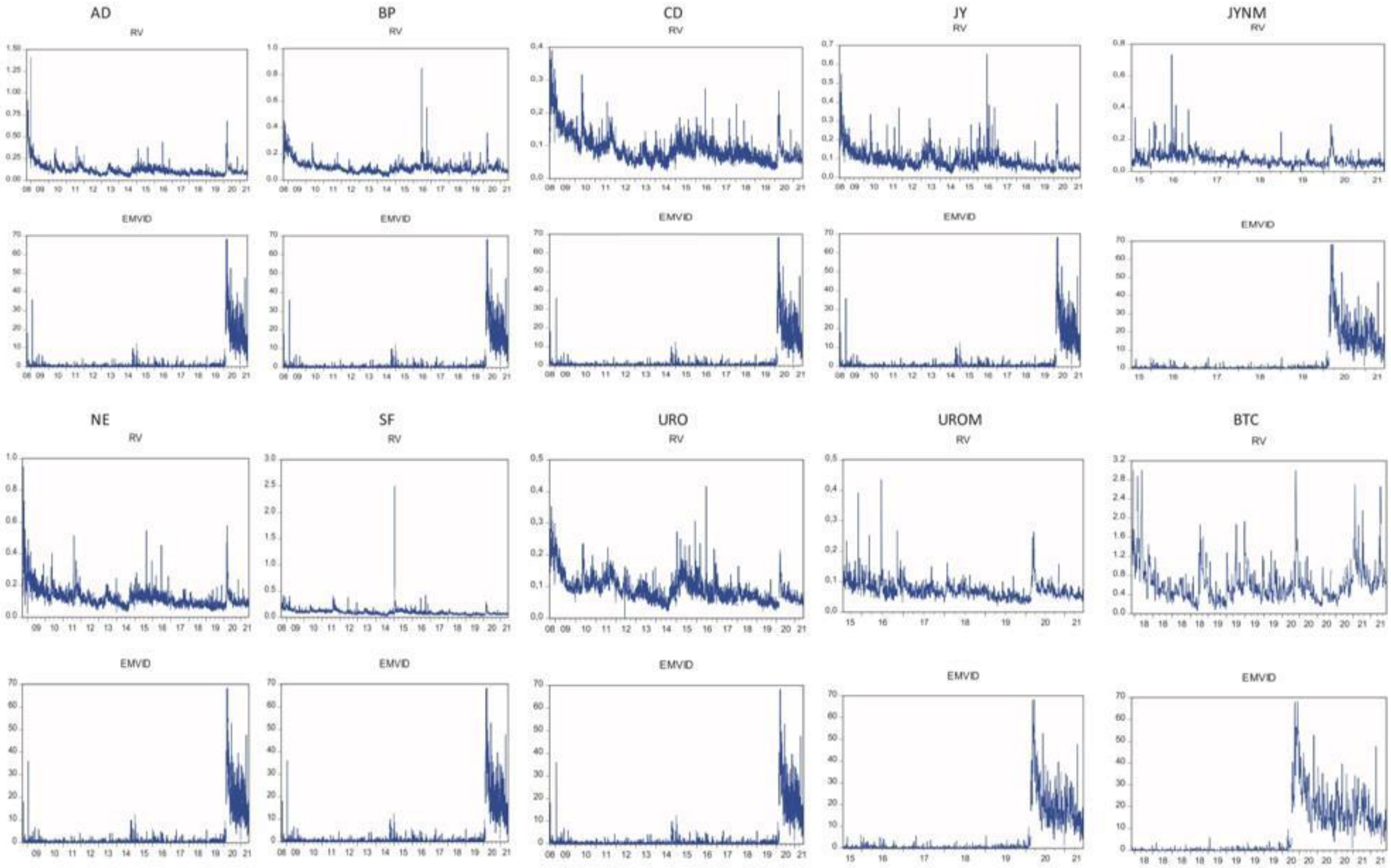
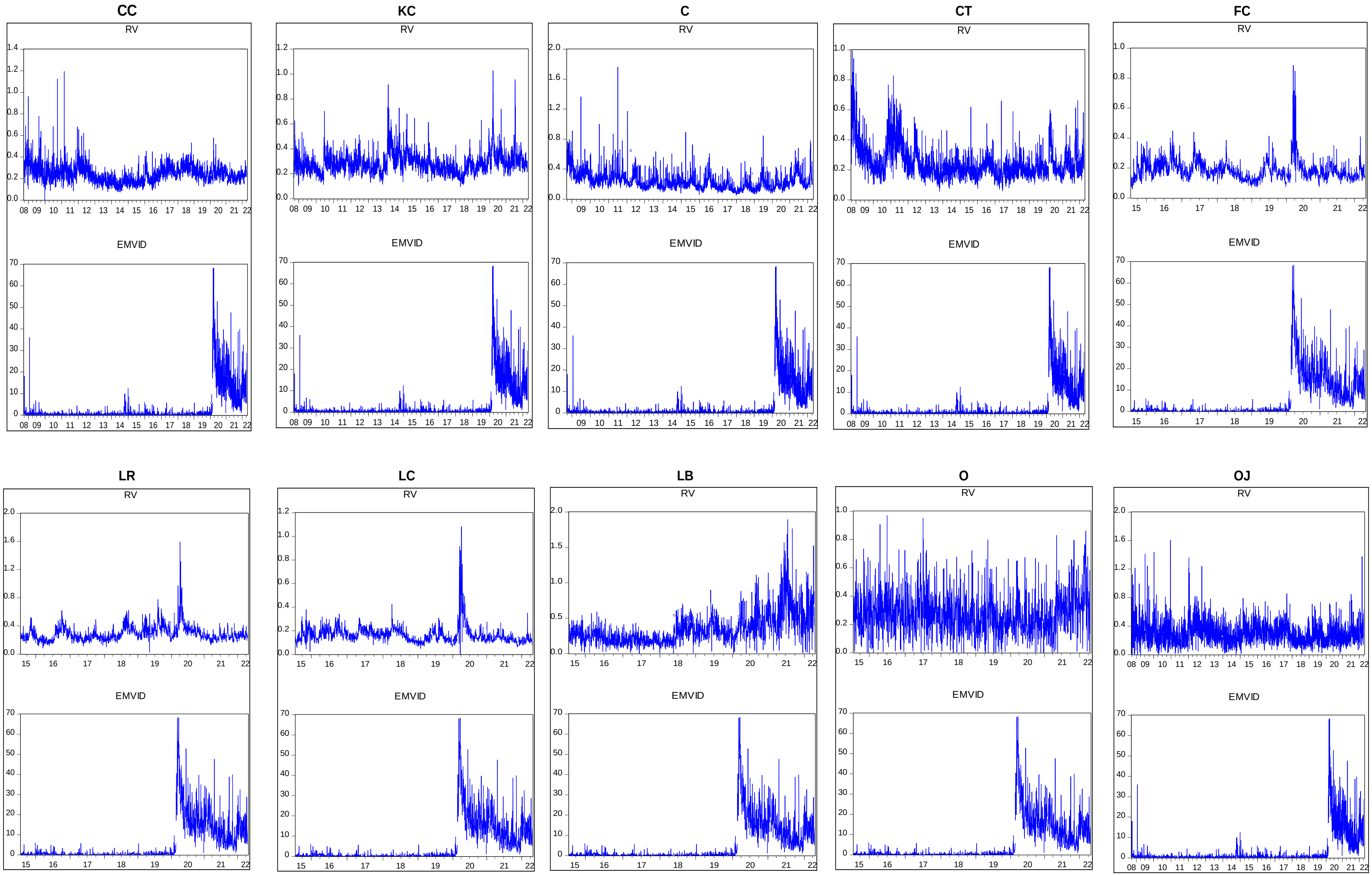


Figure A4.1: Data Plots.

Note: RV depicts the realised volatility of the foreign exchange and Bitcoin futures index. EMVID represents the newspaper-based uncertainty index related to infectious diseases.

Table A5.1: Selected Variables, Acronyms and Sample Coverage

Symbol	Future Index	Sample Period
1. BO	Soybean oil futures	22 September 2008–27 April 2022
2. CC	Cocoa futures	22 September 2008–27 April 2022
3. C	Corn futures	22 September 2008 -27 April 2022
4. CT	Cotton no.2 futures	22 September 2008–27 April 2022
5. FC	Feeder cattle futures	27 September 2015–27 April 2022
6. KC	Coffee c futures	22 September 2008–27 April 2022
7. LB	Lumber futures	27 July 2015–27 April 2022
8. LC	Live cattle futures	27 July 2015–27 April 2022
9. LH	Lean hogs futures	27 July 2015–27 April 2022
10. OJ	Orange juice futures	22 September 2008–27 April 2022
11. O	Oat futures	27 July 2015–27 April 2022
12. SB	Sugar #11 futures	22 September 2008–27 April 2022
13. SM	Soybean meal futures	22 September 2008–27 April 2022
14. S	Soybean futures	22 September 2008–27 April 2022
15. W	Wheat futures CBOT	22 September 2008–27 April 2022


CC
RV
EMVID
KC
RV
EMVID
C
RV
EMVID
CT
RV
EMVID
FC
RV
EMVID
LR
RV
EMVID
LC
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LB
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RV
EMVID
OJ
RV
EMVID

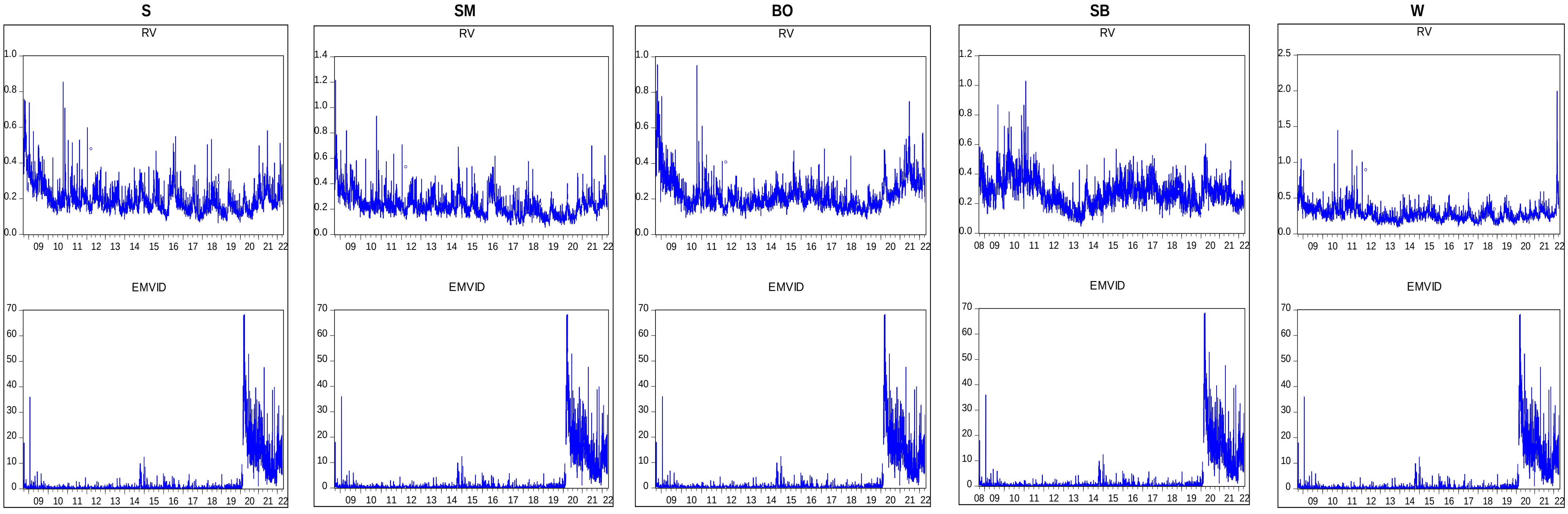


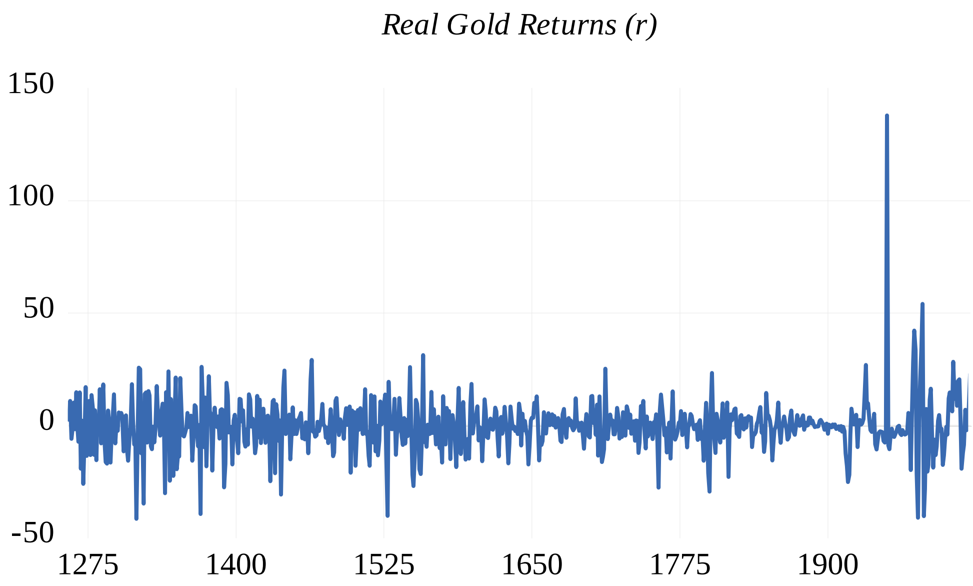
Figure A5.1: Data Plots.

Note: the realised volatility of the agricultural commodity futures is represented by RV. The newspaper-based uncertainty index related to infectious is represented by EMVID.

Table A6.1. Summary Statistics: 1258-2020

	Variable	
Statistic	**Real Gold Returns (*r*)**	**Probability of Fatality (*pf*)**
Mean	-0.2865	0.0006
Median	-0.4400	0.0000
Maximum	137.9596	0.0153
Minimum	-41.5800	0.0000
Std. Dev.	11.5959	0.0027
Skewness	2.1510	5.0134
Kurtosis	30.4436	26.6599
Jarque-Bera	24532.3500***	20992.9400***
Observations	763	763

Note: *** indicates rejection of the null-hypothesis of normality at the 1% level of significance.



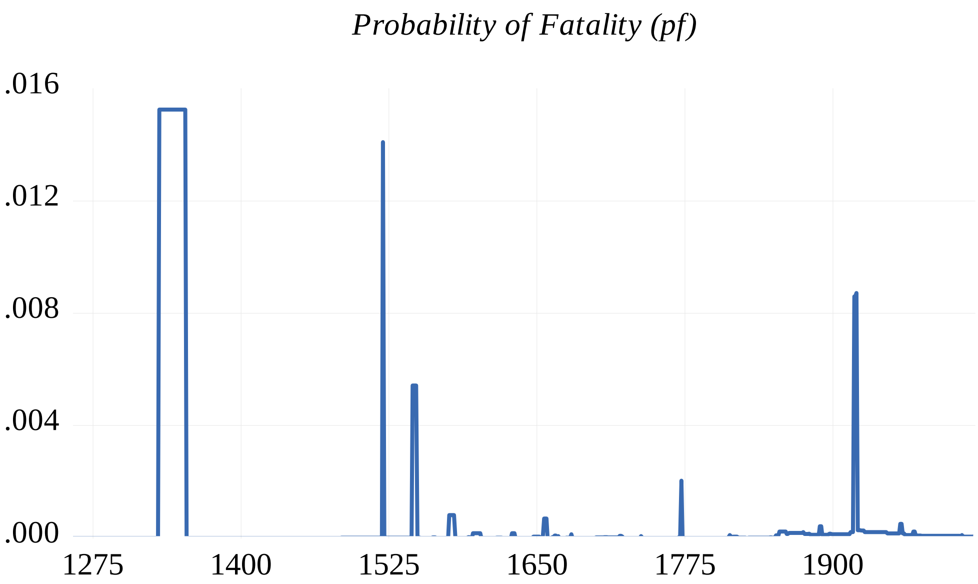


Figure A6.1. Data Plots: 1258-2020

Table A6.2. BDS Test

	Dimension (*m*)				
	2	3	4	5	6
z-statistic	6.6924***	9.9933***	11.5245***	12.5632***	13.5673***

Note: The test is applied to the residuals recovered from the linear regression of real gold returns (*r*) as the dependent variable and one lag of the probability of fatality (*pf*) as the independent variable; *** indicates rejection of the null-hypothesis of *iid* residuals at the 1% level of significance.

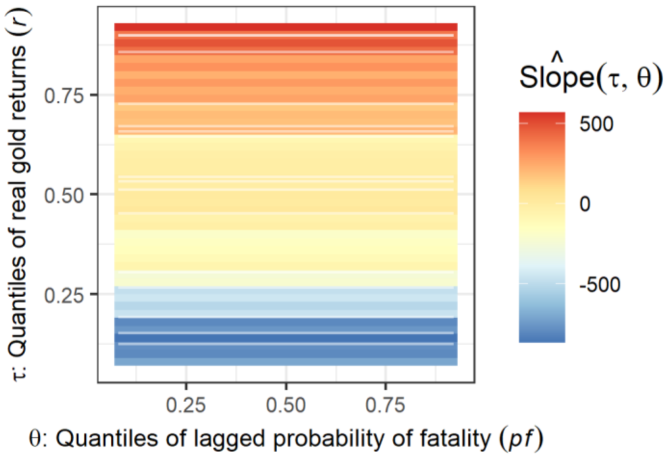


Figure A6.2. Slope Parameter Estimates from Quantile-On-Quantile Regression: Real Gold Returns (*R*) on Lagged Probability of Fatality (*Pf*) Due to Contagious Diseases

Note: See Sim and Zhou (2015) for the complete technical details associated with the estimation of the model.

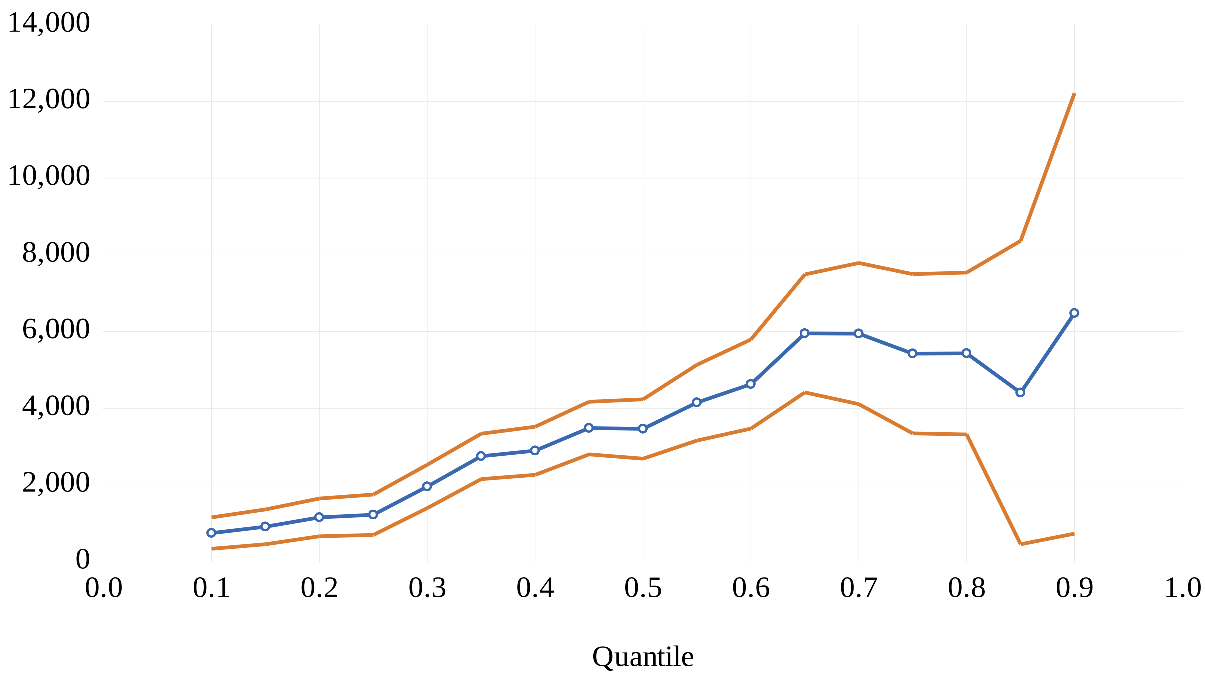


Figure A6.3. Slope Parameter Estimate from Quantile Regression: Real Gold Returns Volatility (*Vr*) on Lagged Probability of Fatality (*Pf*) Due to Contagious Diseases

Note: See Notes to Figure 6.1.

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