Infectious Disease-Related Uncertainty and the Safe-Haven Characteristic of US Treasury Securities

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Abstract

Using daily data from November 1985 to July 2020, we analyse the impact of a daily newspaper-based index of uncertainty associated with infectious diseases (EMVID) on the level, slope and curvature factors derived from the term structure of interest rates of the US covering maturities of 1 year to 30 years. Results from nonlinearity and structural break tests indicate the misspecification of the linear causality model and point to the suitability of applying a time-varying model that is robust to misspecification due to nonlinearity and regime change. We thus use a dynamic conditional correlation-multivariate generalised autoregressive conditional heteroskedasticity (DCC-MGARCH) framework and the results indicate significant predictability of the three latent factors from the EMVID index at each point of the entire sample, and also provide evidence of instantaneous spillover. Finally, we comprehensively determine the safe-haven characteristic of the US Treasury market by analysing the signs of the underlying time-varying conditional correlation between the level, slope and curvature factors and the EMVID index. Results show that US treasuries with long-term maturities as captured by the level factor are consistently negatively correlated with the EMVID index, i.e., they act as a safe-haven, with the slope factor (medium-term maturities) following this trend since 2007, and the slope factor (short-term maturities) also showing signs of a safe-haven since May of 2020. Overall, the findings provide reasonable evidence to imply that US Treasury securities can hedge the risks associated with the financial market in the wake of the current COVID-19 pandemic.

Keywords: Yield Curve Factors; Financial Market Uncertainty; Infectious Diseases; COVID-19; Time-Varying Granger Causality

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1. Introduction

The role of Treasury securities of the United States (US) as a traditional "safe haven" is well-recognized (see for example, Fleming et al. (1998), Hartmann et al. (2004), Baur and Lucey (2010), Noeth and Sengupta (2010), Chan et al. (2011)). Accordingly, investors are often attracted to this asset class because of its ability to offer portfolio diversifications and hedging benefits during periods of turmoil and heightened uncertainties in conventional financial markets. The safe-haven nature of US Treasury securities is primarily due to the significant lack of default risk fuelled by the vast revenue stream generated by the US government, which accounts for over 20 percent of global output (Kopyl and Lee, 2016; Habib and Stracca, 2017; Hager, 2017). In fact, bond market capitalization stands at $40.7 trillion (which is higher than the corresponding value of $30 trillion associated with the stock market), and basically represents nearly two-thirds of the value of the global bond market (Securities Industry and Financial Markets Association (SIFMA)).

The COVID-19 outbreak, starting as a regional crisis in China before swelling to an unprecedented health crisis on a global scale, is not only the first pandemic in the 21st century, but also a human catastrophe. It has devastated hundreds of thousands of lives and jeopardized the lives of millions, making it a public health emergency. On the economic front, the lockdown instituted to contain the spread of the virus has triggered the worst economic downturn since the Great Depression (Caggiano et al., forthcoming). In parallel, financial markets have experienced a substantial and unprecedented spike in uncertainty (Bouri et al., 2020), with stock markets around the globe having plummeted to their lowest levels since the Global Financial Crisis (GFC) of 2007-2009 (Zhang et al., 2020). Furthermore, as pointed out by Baker et al. (2020a), the COVID-19 pandemic has negatively impacted stock markets more than any previous infectious disease outbreak, including the Spanish Flu of 1918. Notably, the unique nature of the joint health and economic crisis resulting from the COVID-19 pandemic and its adverse effects on all sectors of the economy provide a unique research setting to examine whether US Treasury securities can provide protection from stock market losses in the wake of increased financial market uncertainty. Specifically, we aim in this paper to analyse the ability of historical financial market uncertainty related to infectious diseases of various types (such as MERS, SARS, Ebola, H5N1, H1N1, and of course Coronavirus) to predict the daily path of zero coupon US Treasury bond yields over the period 25th November, 1985 to 17th July, 2020.

Econometrically, we use the well-established framework of Nelson and Siegel (1987) from the finance literature to summarize the entire term structure into three latent yield factors of level, slope and curvature, which are considered the only relevant factors that characterize the yield curve (Litterman and Scheinkman, 1991). In this way, we do not restrict ourselves to a specific set of bond yields, but instead use the entire term structure involving interest rates associated with US Treasury securities of maturities ranging from 1 year to 30 years. Once we obtain the three latent factors, we then relate the movement of the level, slope and curvature to a metric of financial market uncertainty related to infectious diseases. In this regard, we use the recently developed newspaper-based index of Baker et al. (2020b), which tracks daily equity market volatility (EMV), in particular the movements in the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), due to infectious diseases. In terms of the predictive framework, we track the historical relationship over the last three and a half decades, using the dynamic conditional correlation-multivariate generalised autoregressive conditional heteroskedasticity (DCC-MGARCH) Hong tests (as developed by Lu et al. (2014)) for time-varying Granger causality. The main appeal of the DCC-MGARCH Hong tests is that we can analyse causality at each point in time in order to pin down the time-varying predictability of financial market uncertainties resulting from infectious diseases. In addition to detecting unidirectional time-varying causality, the tests can also pick-up any evidence of instantaneous information spillover.

While detecting the existence of statistically significant impacts of infectious diseases-based financial market uncertainty on the three latent factors is a necessary step of testing our hypothesis of US Treasuries being safe-havens, sufficiency requires us to determine the sign of this impact. In particular, we want to check whether the yield factors are negatively correlated with the measure of financial market uncertainty due to infectious diseases. Recall that, if US Treasuries are indeed safe-havens, then the demand for zero coupon bonds would increase to hedge against stock market uncertainties due to infectious diseases, and in the process the rising demand would lead to a rise in the prices of US zero coupon bonds and a corresponding decline in their yields. To be consistent with time-varying predictability, we estimate and track the evolution of the sign between the three latent factors and our metric of financial market uncertainty due to infectious diseases using the underlying time-varying conditional correlations obtained from the DCC-MGARCH model.

One must note that, traditionally the safe-haven literature analyses whether the (time-varying) correlation between the returns of a proposed safe-haven like US Treasury securities (and gold, the Swiss Franc, Japanese Yen, and more recently cryptocurrencies such as Bitcoin) is negatively correlated with equity returns during specific episodes such as the GFC or COVID-19 outbreak (e.g., Cheema et al., 2020). We however, take a different and more direct approach by relating the entire yield curve to a measure of economic uncertainty, which in turn is the underlying reason behind the negative impact on stock returns, and hence aim to capture the implicit positive relationship between the zero coupon bond yields of various maturities and equity returns. To the best of our knowledge, this is the first paper to study the predictability of the entire US term structure due to financial market uncertainty resulting from infectious diseases covering 35 years of daily data. In the process, we build on the recent works of Cheema et al. (2020) and Ji et al. (2020). The former shows that composite Treasury bill and Treasury bond indices (corresponding to maturities up to a year and more than 10 years respectively) serve as reliable safe-havens during the GFC and the period associated with the outbreak of the Coronavirus, while the latter depicts evidence of weak safe-haven characteristic for the 3-month Treasury bill yield during the COVID-19 pandemic.

The remainder of the paper is organized as follows: Section 2 discusses the data, along with the basics of the two methodologies associated with the Nelson-Siegel model, and the time-varying DCC-MGARCH Hong tests. Section 3 presents the results, with Section 4 concluding the paper.

2. Data and Econometric Methodologies

In this section we present the data and the basics of the two methodologies used for our empirical analyses, which involves the extraction of the three latent yield curve factors and analysing its time varying predictability due to the metric of uncertainty emanating from infectious diseases.

2.1. Data

We collect daily zero coupon yields of Treasury securities with maturities from 1 year to 30 years to estimate the yield curve factors for the US. The zero coupon bond yields are based on the work of Gürkaynak et al. (2007), and are retrieved from DataStream maintained by Thomson Reuters. Gürkaynak et al. (2007) provide researchers and practitioners with a long history of high-frequency yield curve estimates of the Federal Reserve Board at a daily frequency. They use a well-known and simple smoothing method that is shown to fit the data very well, with the resulting estimates used to compute yields for any horizon.

The daily measure of uncertainty due to infectious diseases (EMVID) is developed by Baker et al. (2020) and publicly available from: http://policyuncertainty.com/infectious_EMV.html, with the index being a newspaper-based infectious disease EMV tracker, available at daily frequency from January, 1985 till recent days. To construct the EMVID, Baker et al. (2020) specify four sets of terms namely, E: economic, economy, financial; M: "stock market", equity, equities, "Standard and Poors"; V: volatility, volatile, uncertain, uncertainty, risk, risky; ID: epidemic, pandemic, virus, flu, disease, coronavirus, mers, sars, ebola, H5N1, H1N1, and then obtain daily counts of newspaper articles that contain at least one term in each of E, M, V, and ID across approximately 3,000 US newspapers. The raw EMVID counts are scaled by the count of all articles on the same day, and finally the authors multiplicatively rescale the resulting series to match the level of the VIX, by using the overall EMV index and scaling the EMVID index to reflect the ratio of the EMVID articles to total EMV articles. Based on the data availability of the two variables under consideration, our analysis covers the sample period 25th November, 1985 to 17th July, 2020.

2.2. Methodology

2.2.1. Extraction of the Yield Curve Factors

The dynamic Nelson-Siegel three-factor model of Diebold and Li (2006) (DNS, hereafter) is applied in this study to fit the yield curve of zero coupon US Treasury securities. The yield curve is decomposed into three latent factors using the Nelson and Siegel (1987) representation in a dynamic form. The DNS with time-varying parameters is represented as:

$$r_t(\tau) = L_t + S_t\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right) + C_t\left(\frac{1-exp^{-\lambda\tau}}{\lambda\tau} - exp^{-\lambda\tau}\right) \quad (1)$$

where r_t represents the yield rate at time t and τ is the time to maturity. The factor loading of L_t is 1 and loads equally for all maturities. A change in L_t can change all yields equally, hence L_t is the level factor that represents the movements of long-term yields. The loading of S_t starts at 1 and monotonically decays to zero. S_t changes the slope of the yield curve, and hence is the slope factor that mimics the movements of short-term yields. The loading for C_t starts at 1 and decays to zero, with a hump in the middle. An increase in C_t leads to an increase in the yield curve curvature, and hence it is the curvature factor that mimics medium-term yield movements. The DNS model follows a VAR process and is modelled in state-space form using the Kalman filter. The measurement equation relating the yields and latent factors is:

$$\begin{pmatrix} r_t(\tau_1) \\ r_t(\tau_2) \\ \vdots \\ r_t(\tau_n) \end{pmatrix} = \begin{pmatrix} 1 & \left(\frac{1-exp^{-\tau_1\lambda}}{\tau_1\lambda}\right) & \left(\frac{1-exp^{-\tau_1\lambda}}{\tau_1\lambda} - exp^{-\tau_1\lambda}\right) \\ 1 & \left(\frac{1-exp^{-\tau_2\lambda}}{\tau_2\lambda}\right) & \left(\frac{1-exp^{-\tau_2\lambda}}{\tau_2\lambda} - exp^{-\tau_2\lambda}\right) \\ \vdots & \vdots & \vdots \\ 1 & \left(\frac{1-exp^{-\tau_n\lambda}}{\tau_n\lambda}\right) & \left(\frac{1-exp^{-\tau_n\lambda}}{\tau_n\lambda} - exp^{-\tau_n\lambda}\right) \end{pmatrix}' f_t + \begin{pmatrix} u_t(\tau_1) \\ u_t(\tau_2) \\ \vdots \\ u_t(\tau_1) \end{pmatrix}, \;\; u_t \sim N(0,R) \quad (2)$$

The transition equation relating the dynamics of the latent factors is:

$$\tilde{f}_t = \Gamma \tilde{f}_{t-1} + \eta_t \qquad \eta_t \sim N(0,G) \qquad (3)$$

where $r_t(\tau)$ and u_t are $m \times 1$ dimensional vectors for yield rates with given maturities (in our case 1 year to 30 year) and the error terms, respectively. The coefficient matrix in the measurement equation follows the structure introduced by Nelson and Siegel (1987), $f_t = [L_t, S_t, C_t]$ is a 3×1 dimensional vector and comprises the yield rate shape parameters which vary over time. Continuing with the transition equation: $\tilde{f}_t = f_t - \overline{f}$ is the demeaned time-varying shape parameter matrix, Γ illustrates the dynamic relationship across shape parameters, η_t is a 3×1 dimensional error vector which is assumed to be independent of u_t, G is a $m \times m$ dimensional diagonal matrix and R is a 3×3 dimensional variance-covariance matrix, allowing the latent factors to be correlated.[1]

2.2.2. Dynamic Conditional Correlation-Multivariate Generalised Autoregressive Conditional Heteroskedasticity (DCC-MGARCH) Hong Tests

After extracting the three latent factors, we analyse the time-varying predictability of the EMVID index of *L*, *S*, and *C*. Following Lu et al. (2014), we consider two stationary time-series (X_t and Y_t), where the former corresponds to the three latent factors considered in turn, and the latter involves the measure of uncertainty associated with infectious diseases. Given $Z_t(j) = \begin{pmatrix} X_t \\ Y_t \end{pmatrix}$, where j represents the lag order used in the dynamic correlation coefficient, the DCC-MGARCH model is defined as follows in line with Engle (2002):

$$Z_t(j)|I_{t-1} \sim N(0, D_{t,j}R_{t,j}D_{t,j})$$

[1] Details of the estimation procedure are beyond the scope of this study, and interested readers are referred to Diebold and Li (2006). Complete details of the parameter estimates of the model are available upon request from the authors.

$$D_{t,j}^2 = diag(\omega_{t,j}) + diag(\kappa_{t,j}) \circ Z_t(j)Z_t{}'(j) + diag(\lambda_{t,j}) \circ D_{t-1,j}^2$$

$$u_{t,j} = D_{t-1,j}^{-1} Z_t(j) \tag{4}$$

$$Q_{t,j} = S \circ (u' - A - B) + Au_{t-1,j}u'_{t-1,j} + BQ_{t-1,j}$$

$$R_t, j = diag(Q_{t,j})^{-1} Q_{t,j} diag(Q_{t,j})^{-1}$$

For the widely used DCC-MGARCH(1,1) model, the dynamic correlation estimator with lag j is:

$$\rho_{pq,t}(j) = \overline{\rho}_{pq}(j) + \alpha_j(u_{p,t-1}u_{q,t-1-j} - \overline{\rho}_{pq}(j)) + \beta_j(\rho_{pq,t-1}(j) - \overline{\rho}_{pq}(j))$$

$$r_{pq,t}(j) \frac{\rho_{pq}(j)}{\sqrt{\rho_{11,t}\rho_{22,t}(j)}} \tag{5}$$

where $p, q = 1,2$.

Based on the choice of a positive integer M and a kernel function $k(x)$, the unidirectional DCC-MGARCH Hong test for Y_t to X_t is denoted as $H_{1,t}(k)$:

$$H_{1,t}(k) = \frac{T\sum_{j=1}^{T-1} k^2\left(\frac{j}{M}\right) r_{12,t}^2(j) - C_{1T}(k)}{\sqrt{2D_{1T}(k)}} \tag{6}$$

where

$$C_{1T}(k) = \sum_{j=1}^{T-1}\left(1 - \frac{j}{M}\right) k^2\left(\frac{j}{M}\right)$$

$$D_{1T}(k) = \sum_{j=1}^{T-1}\left(1 - \frac{j}{T}\right)\left(1 - \frac{j+1}{T}\right) k^4\left(\frac{j}{M}\right)$$

The instantaneous DCC-MGARCH Hong test from Y_t to X_t is denoted as $H_{2,t}(k)$:

$$H_{2,t} = \frac{T\sum_{j=0}^{T-2} k^2\left(\frac{j+1}{M}\right) r_{12,t}^2(j) - C_{1T}(k)}{\sqrt{2D_{1T}(k)}} \tag{7}$$

where $C_{1T}(k)$ and $D_1T(k)$ are estimated in $H_{1,t}(k)$.

Note that, the DCC-MGARCH Hong tests are asymptotically normally distributed. Given that it is not feasible to estimate all lagged dynamic correlations in DCC-MGARCH Hong tests, we follow Hong (2001) to deal with this by choosing a suitable kernel function namely, the Bartlett kernel.[2] It must be pointed out that the choice of non-uniform kernels and M has little impact on the size of the DCC-MGARCH Hong tests.

3. Empirical Results

The data for the three yield curve factors of level, slope and curvature, and the EMVID index are summarized in Table A1, and plotted in Figure A1 in the Appendix. Among the dependent variables, the mean value of the slope factor is negative, indicating that, on average, yields increase along with maturities. The curvature associated with medium-term maturities has a higher average value than the level factor, which corresponds to long-term yields. This result, which is in line with Kim and Park (2013) who also use daily bond yields of the US, is indicative of liquidity issues for bonds with very long maturities. The curvature factor is the most volatile of the three factors, followed by the slope and level. Due to the overwhelming rejection of the null hypothesis of normality under the Jarque-Bera test, all variables are non-normal. Moreover, based on the augmented Dickey-Fuller (ADF) test of Dickey and Fuller (1979), all four variables of concern are found to be stationary at the highest level of significance, and hence can be used directly for the time-varying tests of Granger causality without any further transformation of the data.

Before we discuss the findings from the DCC-MGARCH Hong time-varying tests, for the sake of completeness and comparability, we conduct the standard linear Granger causality test, with a lag-length of 7, as determined by the Akaike information criterion (AIC). The resulting $\chi^2(7)$ statistics involving the causality running from the EMVID index to L_t, S_t, and C_t are found to be 0.9023, 0.9725, and 1.6121, with p-values of 0.9963, 0.9953, and 0.9782, respectively. The null hypothesis, that the EMVID index does not Granger cause the three latent factors of the yield curve considered in turn in a bivariate set-up, thus cannot be rejected at the conventional 5% level of significance or even at the 10% level. Therefore, based on the standard linear test, we conclude no significant uncertainty related to infectious disease-related effects on the predictability of the level, slope or curvature of the US yield curve.

Given the insignificant results obtained from the linear causality tests, we statistically examine the presence of nonlinearity and structural breaks in the relationship between the three latent factors of the term structure with the three shocks. Nonlinearity and regime changes, if present, would motivate the use of the time-varying DCC-MGARCH Hong tests, with this framework

[2] The Bartlett kernel is defined as: $k(z) = \begin{cases} 1-|z|, & if\ |z|<1 \\ 0, & if\ |z|>1 \end{cases}$.

formally addressing the issues of nonlinearity and structural breaks in the relationship between the variables under investigation in a bivariate set-up. For this purpose, we apply the Brock et al. (1996) (BDS) test on the residuals from the L_t, S_t, and C_t equations involving 7 lags of the three factors and the EMVID index in the two-variable model. Table A2 in the Appendix presents the results of the BDS test of nonlinearity. The results indicate strong evidence, at the highest level of significance, for the rejection of the null hypothesis of *i.i.d.* residuals at various embedded dimensions (m), which, in turn, is indicative of nonlinearity in the relationship between the factors and the EMVID index. To further motivate the time-varying approach, we use the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003), to detect 1 to M structural breaks in the relationship between L_t, S_t, and C_t with the EMVID index, allowing for heterogenous error distributions across the breaks, and 5% endpoint trimming. When we apply these tests to the L_t, S_t, and C_t equations involving 7 lags of the three factors and the uncertainty index associated with infectious diseases in a bivariate structure, we detect 3, 1 and 2 breaks at 05/02/1993, 06/04/1995, 15/09/2006; 10/12/2008; and 05/02/1993, 23/01/1995 in the L_t, S_t, and C_t equations respectively.

Given the strong evidence of nonlinearity and structural breaks in the relationship between the latent factors and the EMVID index, we now turn our attention to the time-varying tests of Granger causality. In sub-figures (a) and (b) of each of the main Figures (1), (2) and (3), we plot the unidirectional, and instantaneous time-varying DCC-MGARCH Hong tests for information spillover from the EMVID index to L_t, S_t, and C_t respectively, by setting M=7, in accordance with the lag-length of the static test. The top panel of each figure depicts the value of the time-varying DCC-MGARCH Hong test (indicated as the causality test statistic), and at the bottom of each figure, we show shaded regions representing periods during which the test is statistically significant at the 5% level. On the whole, unlike the linear Granger causality test results, there is overwhelming evidence of time-varying information spillover from the EMVID index to all three latent factors both in the traditional causal sense, as well as in an instantaneous fashion. In other words, uncertainty in the financial market due to infectious diseases affects the US Treasuries of all maturities, given the impact of the EMVID index on slope, curvature and level factors corresponding to short-, medium, and long-term maturities.

Although robust predictive inference is derived based on the time-varying DCC-MGARCH Hong tests, it is also interesting to estimate the sign of the effects of the EMVID index on the level, slope and curvature over time. This is especially important in the process of trying to gauge the safe-haven characteristics of the US government bonds of various maturities, since heightened uncertainty should reduce the yields following increases in bond returns due to higher demand. In this regard, to start, we estimate a linear model where we regress the EMVID index on *L*, *S*, and *C* in turn based on ordinary least squares (OLS) with Newey and West (1987) heteroskedasticity and autocorrelation (HAC)-corrected standard errors. The corresponding coefficients of the response of *L*, *S*, and *C* to EMVID is found to be -0.0323, 0.0104, and -0.1510 respectively, with all being significant at the highest level of significance. In other words, these results tend to suggest the safe-haven nature of US Treasuries with medium and long-term maturities, but not so for the same with short-term maturity. But these are time-invariant results for the overall sample period, and to decisively conclude the safe-haven nature of the US Treasuries of the three maturities, we need to take a time-varying approach. This is because there could be specific periods associated with heightened uncertainties due to the outbreak of various infectious diseases, where we might end up with signs of these responses that are different from the average estimates. To this end, we obtain the underlying median estimate of the DCC, along with the 95% confidence bands, based on a Bayesian estimation as outlined in detail in Balcilar et al. (2018).[3] The results are reported in Figure 4, with panels (a), (b) and (c), corresponding to the time-varying responses of *L*, *S*, and *C* to the EMVID index. As can be seen from the plots, consistent with the significant causal impact of EMVID on the three latent factors, the DCCs are significant throughout the sample period (with the confidence bands basically overlapping with the median estimates). While the level factor associated with the long-term US Treasury securities is indicative of being a safe-haven consistently, barring some specific periods, the slope factor capturing the short-term maturities paints the opposite picture. In other words, while long-term yields are negatively correlated with the uncertainty due to infectious diseases, sort-term yields are found to be positively correlated. The DCC estimate of the curvature factor oscillates between positive and negative values over the entire sample period, with the strength of the latter sign being generally higher. But, if we look at the last two decades, which covers the period including all recent global major infectious disease outbreaks, such as the SARS in 2003, Avian flu towards the end of 2003, Swine flu in 2009-2010, MERS Coronavirus (MERS-CoV) in 2012-present, Bird flu in 2013, Ebola virus disease (EVD) in 2014-2016, and finally the Coronavirus disease (COVID-19) in 2019-present, the role of medium- and long-term government bonds as safe-havens is strongly evident. In fact, if we concentrate on the period 2nd January, 2020 to 17th July, 2020, i.e., the period associated with the COVID-19 outbreak, even the government yields associated with short-term

[3] Complete details of the parameter estimates of the Bayesian DCC-GARCH models are available upon request from the authors.

maturities are found to be negatively related to the EMVID index from late-May till the end of our sample period, suggesting their weak safe-haven characteristic during the ongoing pandemic. This finding is in support of the findings of Cheema et al. (2020) and Ji et al. (2020) for composite Treasury bill and Treasury bond indices, and the 3-month Treasury bill yield respectively. To drive home our point, in Figure 4(d), we plot the median DCC estimates starting in January, 2020 till the end of our sample in July, 2020. This figure tends to suggest that, during the current period of the Coronavirus outbreak, medium-term government bonds have consistently acted as a safe-haven, followed by the US Treasuries with long-term maturities (which show some days of positive correlation), with the same also observed to a certain degree for the short-term maturities.

4. Conclusion

In this paper, we analyse the role of US Treasury bonds acting as safe-havens in the wake of the financial market uncertainty that results from infectious diseases, which understandably, is very relevant in the wake of the ongoing pandemic of COVID-19. To test our hypothesis, instead of relying on zero coupon government bond yields of a specific maturity or a small set of maturities, we look at the entire term structure of interest rates associated with 1 year to 30 years of maturity, by obtaining three latent factors of level, slope and curvature. We then analyse the predictability of these three factors, corresponding to long-, short- and medium-term maturities respectively, emanating from a newspapers-based index (EMVID) of financial market uncertainty due to infectious diseases (such as COVID-19, MERS, SARS, Ebola, H5N1, and H1N1). Based on linear Granger causality tests applied to daily data covering the period 25th November, 1985 to 17th July, 2020, we find no evidence of the EMVID index containing any predictive information for the three latent factors. However, we indicate that the linear model is misspecified due to structural breaks and uncaptured nonlinearity. Given this, we use the time-varying DCC-MGARCH Hong tests, which are robust by design to these misspecifications. The time-varying tests however, reveal a completely different picture as they suggests strong evidence of predictability of the three latent factors due to the EMVID index at virtually every point of the entire sample. The uniqueness of this test also highlights the existence of instantaneous spillover from uncertainty to level, slope and curvature. While this information about predictive content is important, to validate the claims of the US Treasury securities being safe-havens historically, we must ensure that the yields are negatively related to financial market uncertainties, as this would suggest higher bond returns due to greater demand, when investment in stock markets is perceived as risky. To delve into this issue, we analyse the signs of the underlying time-varying DCC over the entire sample period between level, slope and curvature factors and the EMVID index. We find that government bonds with long-term maturities, as captured by the level factor, consistently act as a safe-haven, with the medium-term maturities following this trend since September, 2007 (though some evidence of this is also observed earlier in the sample). The slope factor is generally positively related to the EMVID index, suggesting that government bonds with short-term maturities tend to behave like the traditional financial markets. However, since mid-May (January) of this year, the US Treasuries with short-term maturities too (along with the medium- and long-term maturities) are found to act as safe-havens, with the respective yields found to be negatively related to the metric of financial market uncertainty associated with infectious diseases. All in all, we provide strong evidence in favour of using US Treasury securities to hedge financial market risks in the current uncertain environment associated with COVID-19 which has resulted in massive global stock market dips and volatility.

Understandably, our findings at high-frequency, i.e., daily data, have multi-dimensional implications. The observation that financial market uncertainty due to infectious diseases contains predictive information about the evolution of future interest rates in a time-varying set-up can help policymakers fine-tune their monetary policy models, given that these forms of uncertainty affect the slope factor of the yield curve, which captures movements of short-term interest rates. Moreover, evidence of the ability of the EMVID index to predict the level, slope and curvature factors, and the fact that the entire yield curve is considered a predictor of economic activity (Hillebrand et al., 2018) should allow authorities to design policies in a timely-manner to prevent economic recessions, by making high-frequency predictions of low-frequency real economic variables using mixed data sampling (MIDAS) models (Caldeira et al., forthcoming). Further, bond investors can improve their investment strategies by exploiting the role of the EMVID index in their interest-rate prediction models, while risk managers can develop asset allocation decisions conditional on the movements of this index. Our findings also imply that portfolio managers need to incorporate into their portfolio decisions the government bonds of various maturities, with particular emphasis on medium- and long-term maturities to safeguard the value of their portfolios, given the historical ability of these assets to act as safe-havens. However, in the context of the current pandemic, even short-term maturities can be considered as part of portfolios. Finally, researchers may utilize our findings to explain deviations from asset-pricing models by embedding the information of financial market uncertainty due to infectious diseases into their pricing kernels, which, however, need to be time-varying, i.e., nonlinear.

While we concentrate on US Treasury securities, it would be interesting to extend our analysis to other popular safe havens such as gold (and other precious metals), the Swiss Franc and Japanese Yen, and even the leading cryptocurrency Bitcoin, which too has recently gained some popularity as a hedge against financial market risks.

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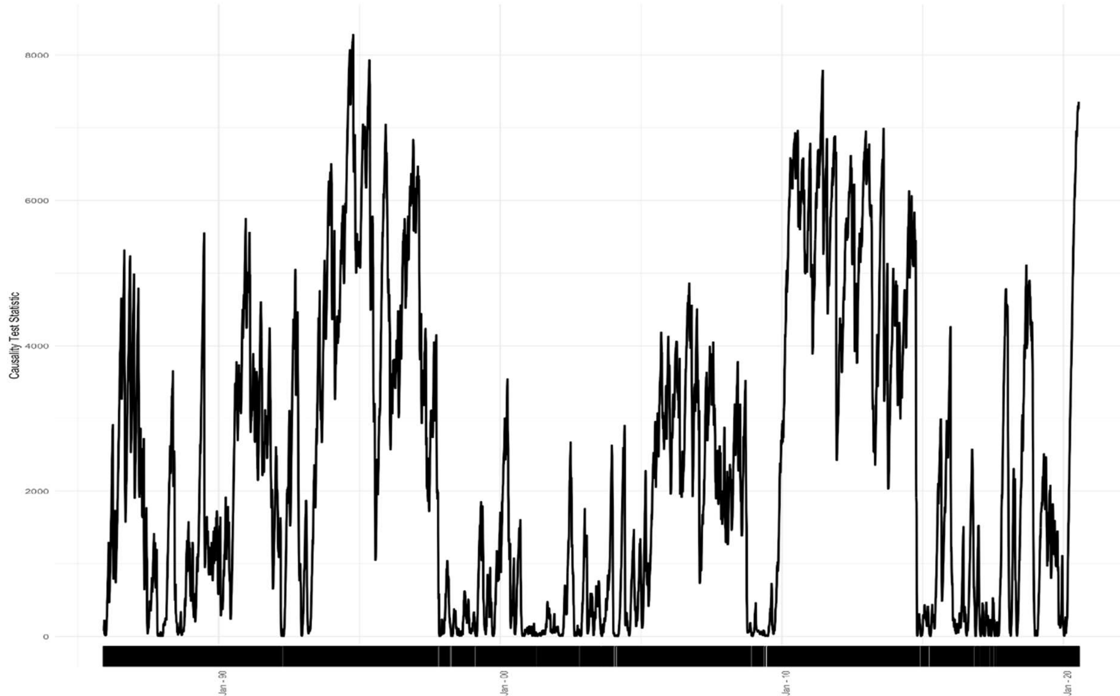
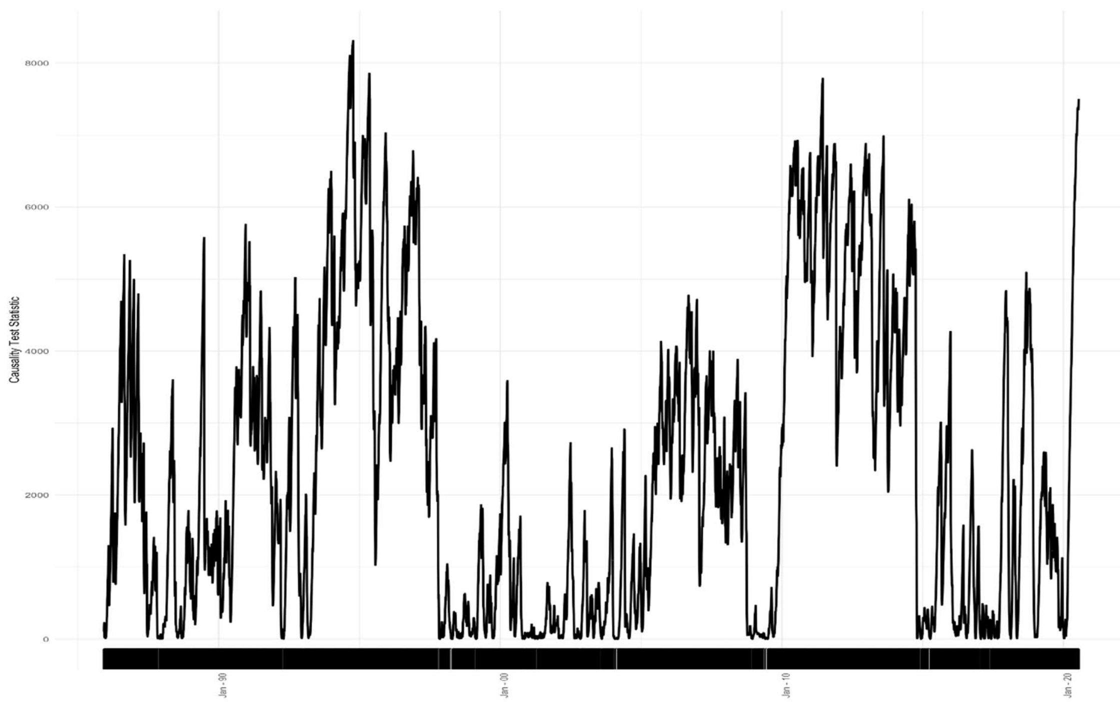
Figure 1. Results of the DCC-MGARCH Hong Tests from the Equity Market Volatility due to Infectious Diseases (EMVID) Index to the Level Factor

1(a). Unidirectional Causality Test: EMVID Index to the Level Factor



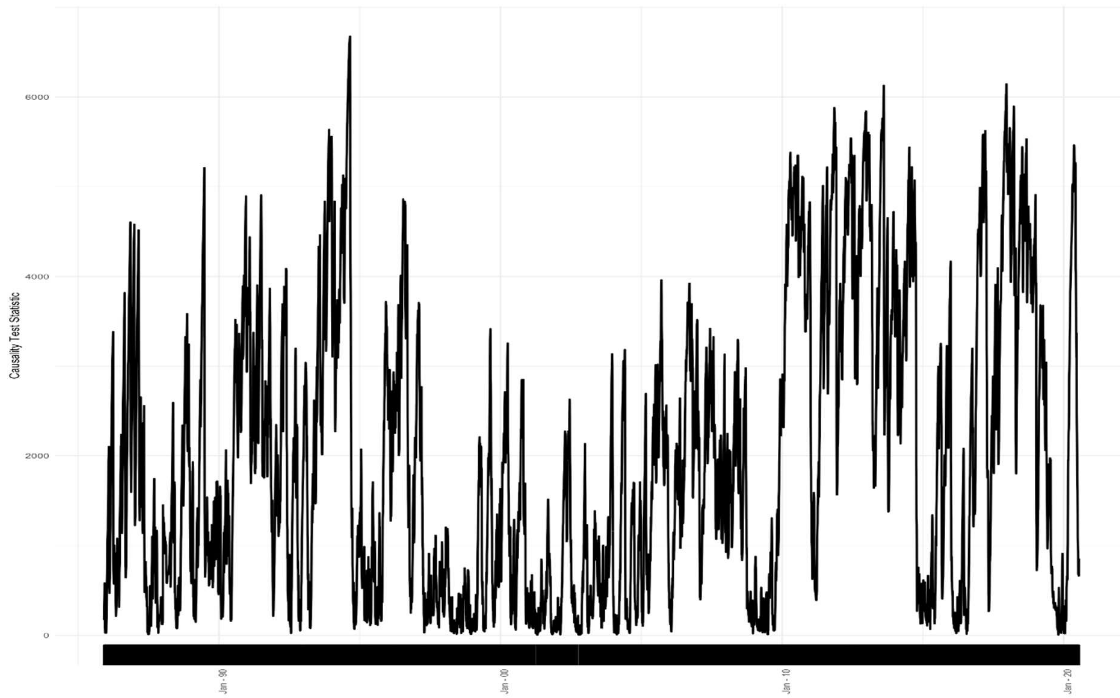
1(b). Instantaneous Causality Test: EMVID Index to the Level Factor



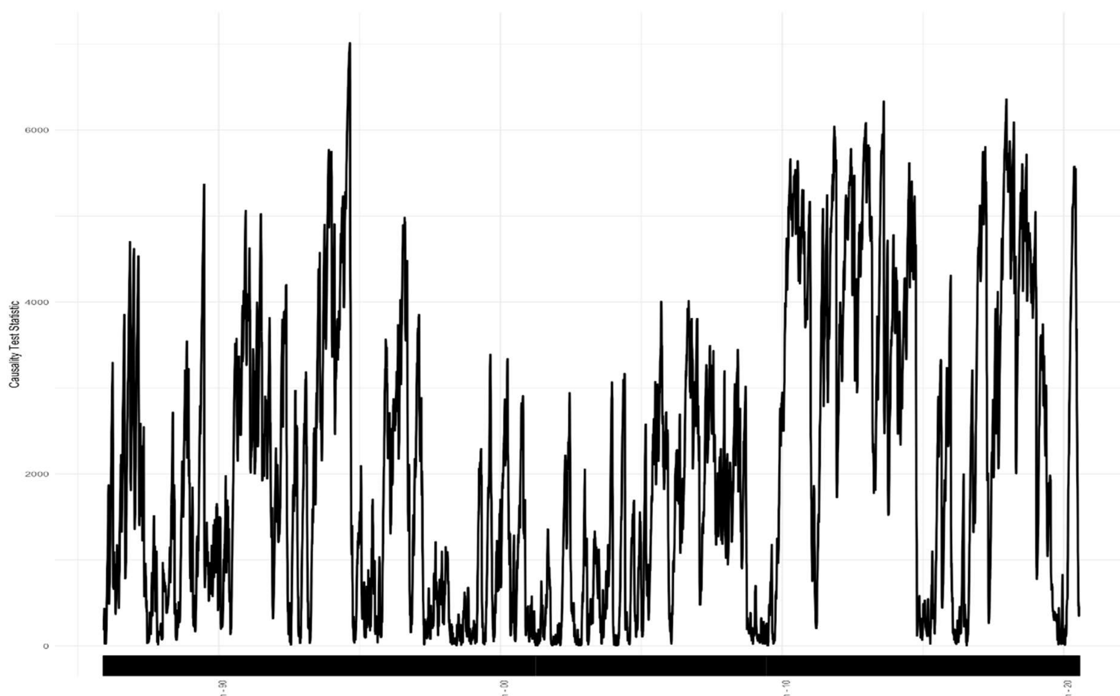
Note: The top panel in the Figures show the time-varying DCC-MGARCH Hong test statistic (causality test statistic); the shaded region below shows the period during which the test is statistically significant at the 5% level.

Figure 2. Results of the DCC-MGARCH Hong Tests from the Equity Market Volatility due to Infectious Diseases (EMVID) Index to the Slope Factor

2(a). Unidirectional Causality Test: EMVID Index to the Slope Factor



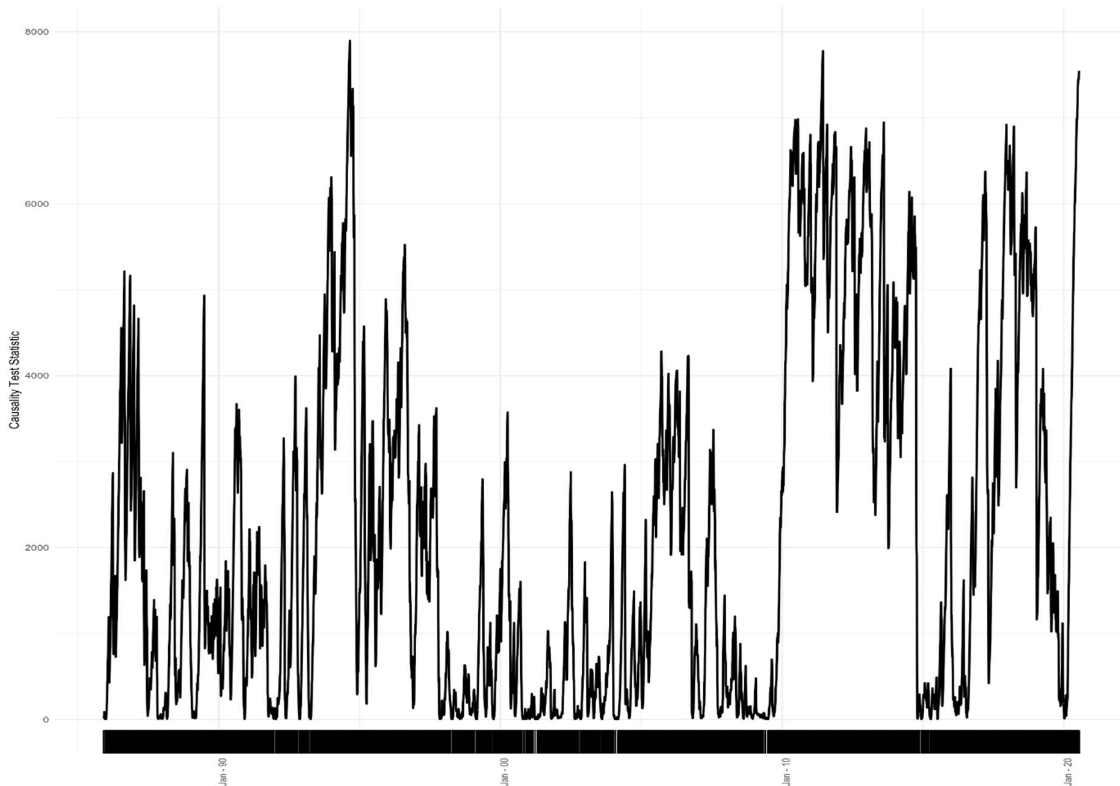
2(b). Instantaneous Causality Test: EMVID Index to the Slope Factor



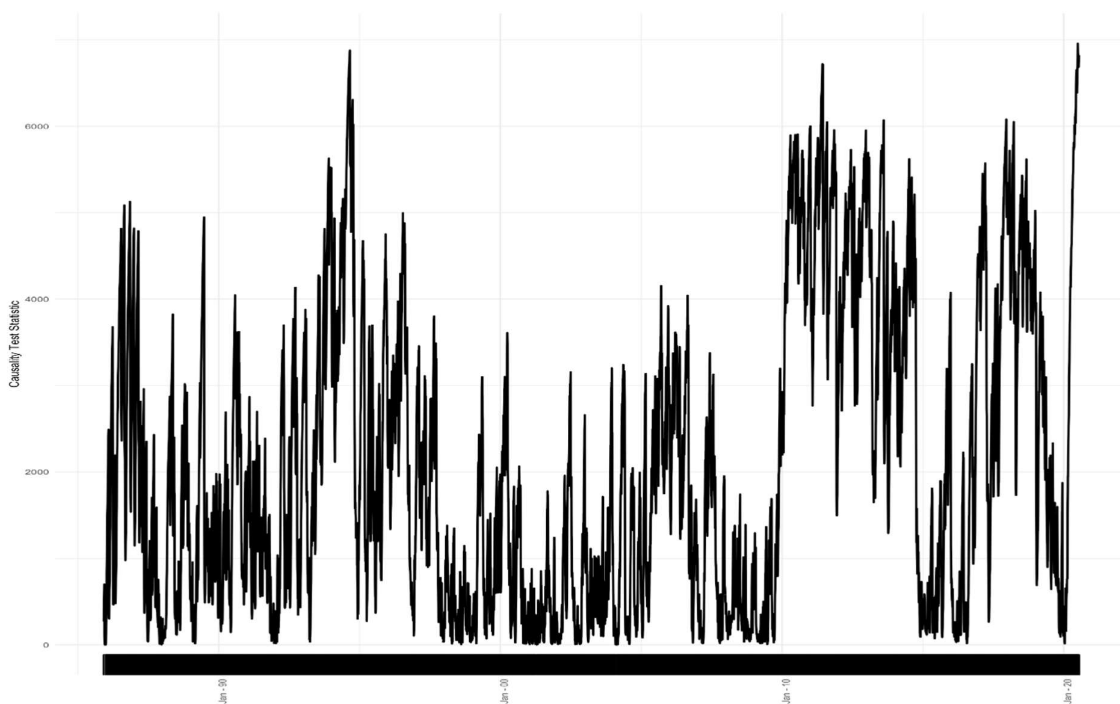
Note: See Notes to Figure 1.

Figure 3. Results of the DCC-MGARCH Hong Tests from the Equity Market Volatility due to Infectious Diseases (EMVID) Index to the Curvature Factor

3(a). Unidirectional Causality Test: EMVID Index to the Curvature Factor



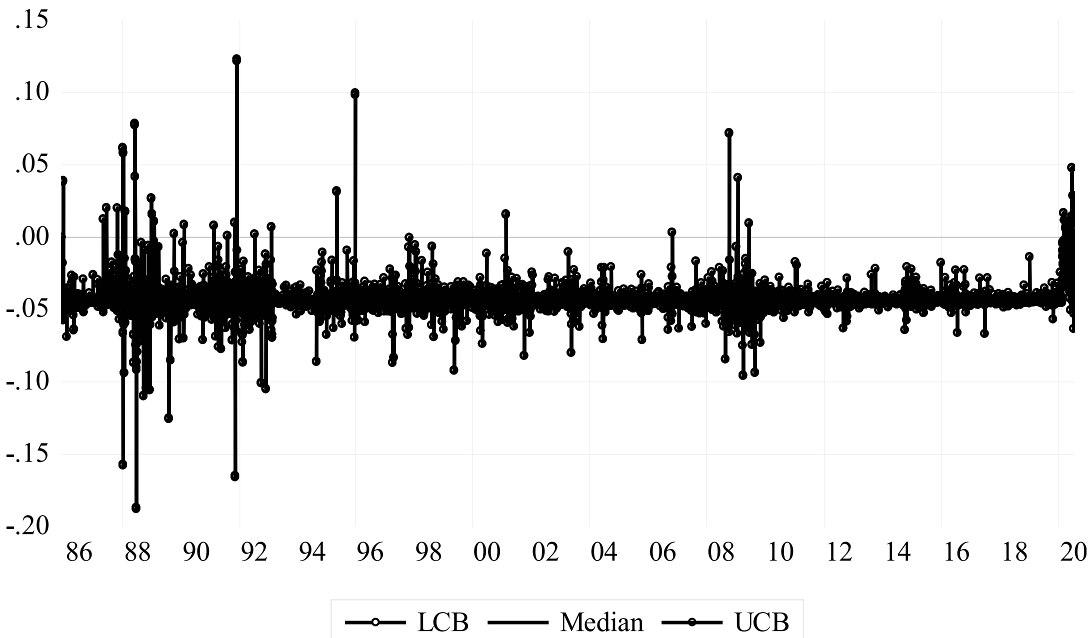
3(b). Instantaneous Causality Test: EMVID Index to the Curvature Factor



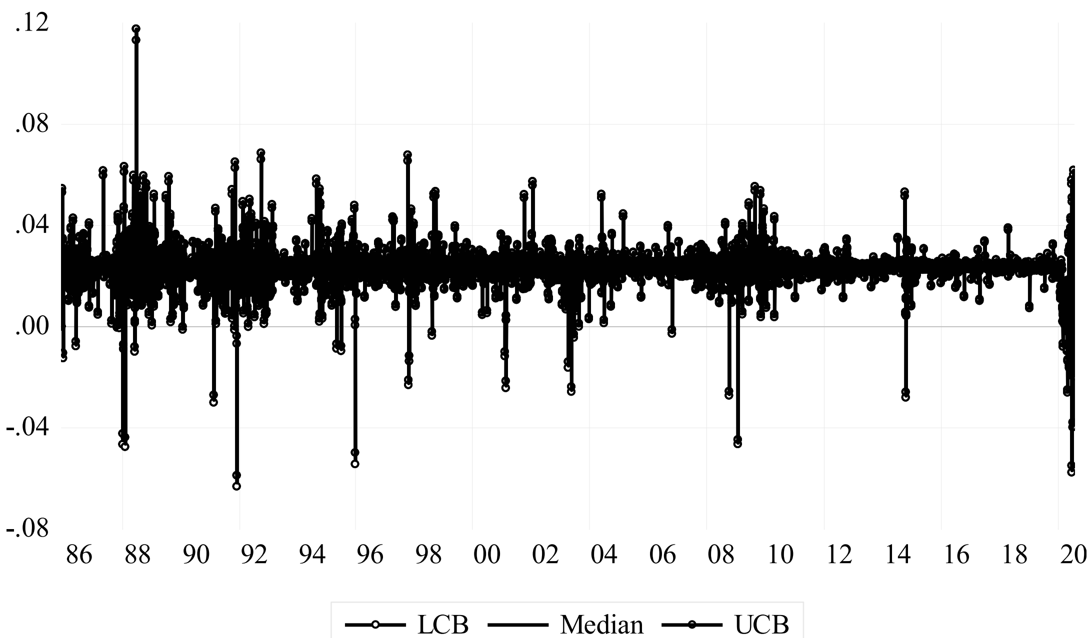
Note: See Notes to Figure 1.

Figure 4. Dynamic Conditional Correlations (DCCs) between Level, Slope and Curvature Factors and the Equity Market Volatility due to Infectious Diseases (EMVID) Index

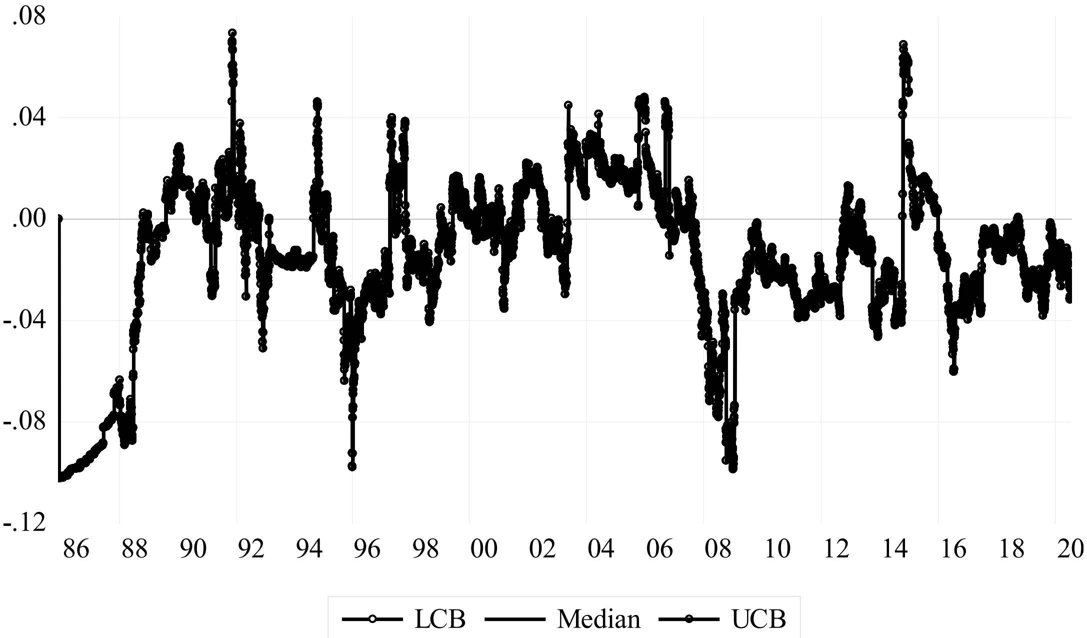
4(a). DCCs between the Level Factor and the EMVID Index: Full-Sample



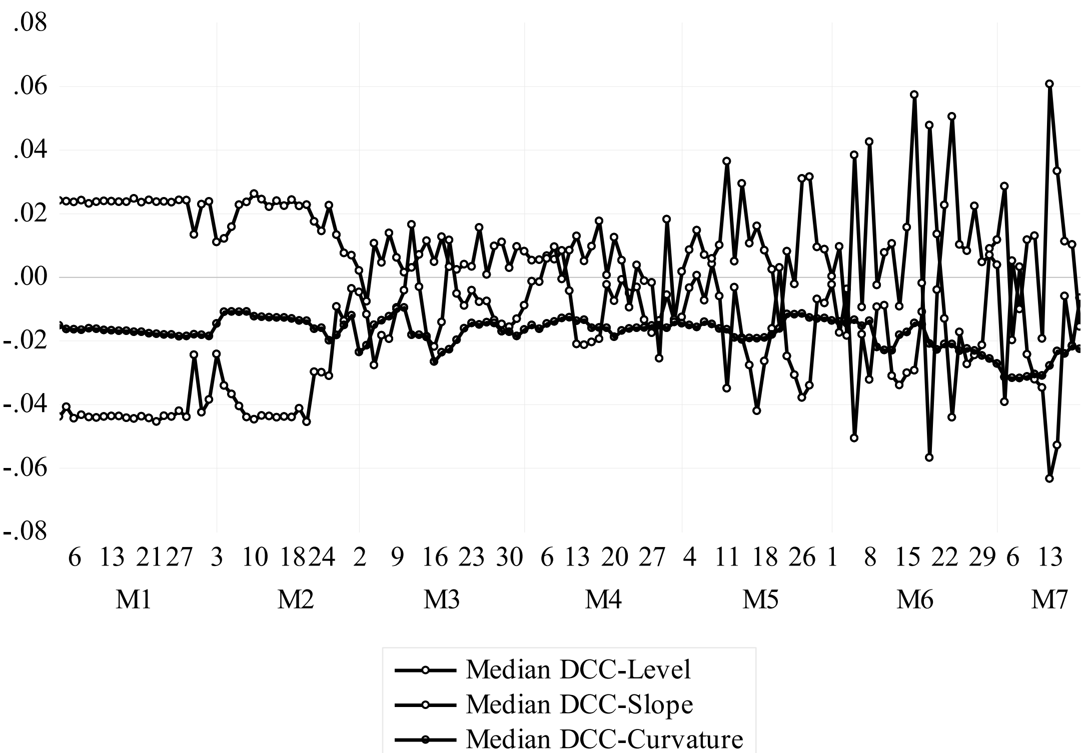
4(b). DCCs between the Slope Factor and the EMVID Index: Full-Sample



4(c). DCCs between the Curvature Factor and the EMVID Index: Full-Sample



4(d). Median DCC estimates between the Level, Slope and Curvature Factors with the EMVID Index: COVID-19 Period (2nd January, 2020 – 17th July, 2020)



Note: LCB, median, and UCB stand for 95% lower confidence band, median estimate of the DCC, 95% upper confidence band in Figures 4(a)-4(c); M1-M7 correspond to the 1-7 months of 2020, while median DCC-level, median DCC-slope, and median DCC-curvature, are the median DCC estimates between the level, slope and curvature factors respectively with the EMVID index in Figure 4(d).

APPENDIX:

Table A1. Summary Statistics

	Variable			
Statistic	Level	Slope	Curvature	EMVID Index
Mean	2.5351	-1.1521	8.2426	0.0024
Median	2.6493	-1.5435	9.3066	0.0358
Maximum	6.1090	6.1745	27.2988	17.4887
Minimum	-6.1235	-4.8061	-4.2672	-17.7642
Std. Dev.	1.6891	1.7062	5.3420	2.0846
Skewness	-1.5885	0.5813	-0.1545	-0.0644
Kurtosis	7.5039	2.8111	3.3143	8.4963
Jarque-Bera	5964.3060***	272.3718***	38.1354***	5934.3570***
ADF Test Statistic	-4.6456***	-4.2892***	-5.2552***	-5.3982***
Observations	8645 (25th November, 1985 - 17th July, 2020)			

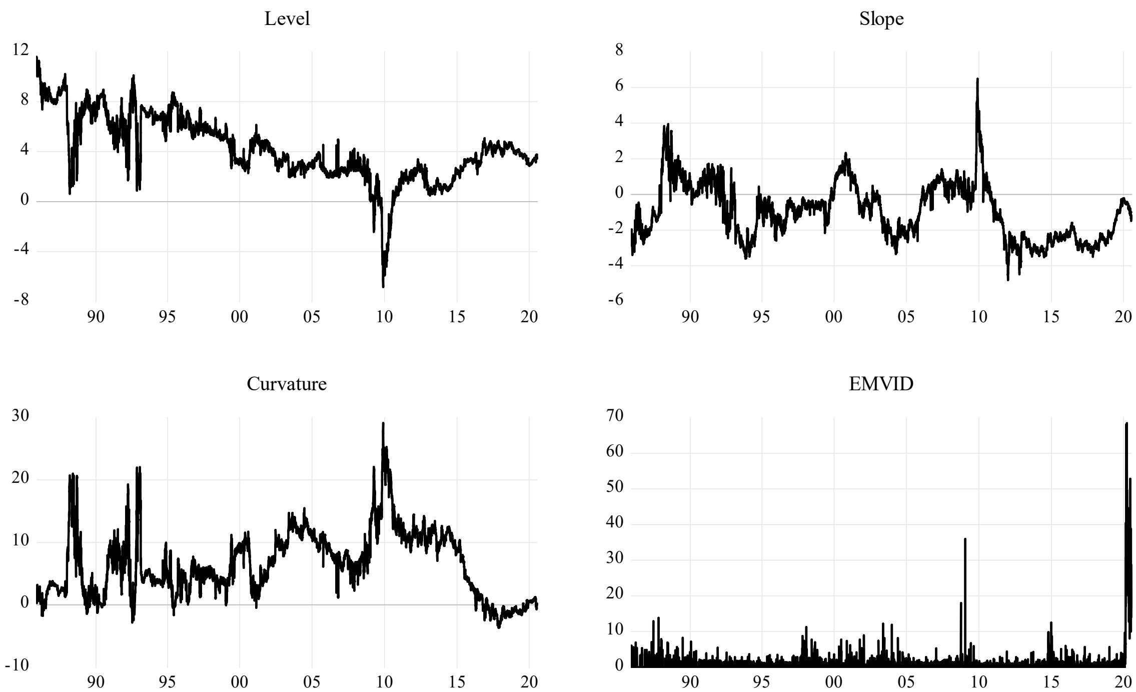
Note: EMVID is the newspapers-based index of financial market uncertainty due to infectious diseases; *** indicates rejection of the null hypothesis of normality at 1% level of significance.

Table A2. Brock et al. (1996) (BDS) Test of Nonlinearity

		Dimension (m)				
Dependent Variable	Independent Variable	2	3	4	5	6
Level	EMVID	36.4389***	44.3044***	50.6968***	56.8966***	63.7261***
Slope	EMVID	33.9308***	41.1193***	47.0493***	53.0809***	59.6194***
Curvature	EMVID	34.4449***	41.8365***	47.5886***	54.0000***	59.2684***

Note: See Notes to Table A1; **e**ntries correspond to the *z*-statistic of the BDS test with the null hypothesis of *i.i.d.* residuals, with the test applied to the residuals recovered from the three yield curve factor equations with 7 lags each of level, slope and curvature, and EMVID index; *** indicates rejection of the null hypothesis at 1% level of significance.

Figure A1. Data Plots



Note: See Notes to Table A1.