Forecasting Power of Infectious Diseases-Related Uncertainty for Gold Realized Variance[#]

Elie Bouri[a], Konstantinos Gkillas[b], Rangan Gupta[c] and ChristianPierdzioch[d]

[a]Adnan Kassar School of Business, Lebanese American University, Lebanon
[b]Department of Management Science and Technology, University of Patras, Megalou Aleksandrou 1, Koukouli, 26334 Patras, Greece
[c]Department of Economics, University of Pretoria, Pretoria, 0002, South Africa
[d]Department of Economics, Helmut Schmidt University, Holstenhofweg 85, P.O.B. 700822, 22008 Hamburg, Germany

Highlights

- We examine the forecasting power of a daily newspaper-based index of uncertainty associated with infectious diseases for gold.
- EMVID index increases realized variance at the highest level of statistical significance.
- EMVID index improves the forecast accuracy of gold realized variance at short-, medium, and long-run horizons.

Abstract

We examine the forecasting power of a daily newspaper-based index of uncertainty associated with infectious diseases (EMVID) for gold market returns volatility via the heterogeneous autoregressive realized variance (HAR-RV) model. Our results show that the EMVID index increases realized variance (RV) at the highest level of statistical significance within-sample, while it improves the forecast accuracy of gold realized variance at short-, medium-, and long-run horizons in a statistically significant manner. Importantly, by assessing the role of this index during the recent pandemic, we find strong evidence for its critical role in forecasting gold RV. Such evidence has important portfolio implications for investors during the current period of unprecedented levels of uncertainty resulting from the outbreak of COVID-19.

Keywords: Uncertainty; Infectious Diseases; COVID-19; Gold; Realized Variance; Forecasting

JEL Codes: C22; C53; D80; Q02

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1. Introduction

The role of gold as a traditional "safe haven" is well-recognized (see Jaffe, 1989; Baur and Lucey, 2010; Baur and McDermott, 2010, Bouri et al., 2019; Gkillas and Longin, 2019; Boubaker et al., 2020; Shahzad et al., 2020), which implies that investors are often attracted to this precious metal due to its ability to offer portfolio diversification and/or hedging benefits during periods of economic slowdown, turmoil in traditional financial markets, increased geopolitical risk or economic uncertainty, and the high degree of risk aversion associated with low investor sentiment (Tiwari et al., 2020; Bonato et al., 2020a). Naturally, an accurate forecast of the volatility of gold returns is of tremendous interest to investors and portfolio managers in the pricing of gold derivatives as well as in designing hedging strategies to mitigate portfolio risks. Not surprisingly, there exists a large body of literature in empirical finance that aims to forecast gold-returns volatility based on various metrics that capture uncertain environments involving financial markets and the macroeconomy (see, for example, Pierdzioch et al., 2016; Fang et al., 2018; Asai et al., 2019; 2020; Demirer et al., 2019; Gkillas et al., 2019; Bonato et al., 2020b).

Recently, the COVID-19 pandemic has triggered a massive spike in the uncertainty associated with every aspect of human life ranging from health to livelihoods, and with the performance of the economy in general[1]. However, there is a lack of empirical evidence on the ability of the uncertainty related to epidemic and pandemic diseases to forecast the realized variance of gold returns. Given this, the objective of our paper is to assess, for the first time, the ability of historical uncertainty related to infectious diseases of various types (such as MERS, SARS, Ebola, H5N1, H1N1, and of course the Coronavirus) to predict the path of gold-returns volatility, with the gold price seeing a steady surge from the beginning of 2020, and particularly from late March.

A necessary first step is to quantify the uncertainty related to infectious diseases in a way that acts as a suitable input into a statistical model for forecasting gold-returns volatility. For this, we use the recently developed newspaper-based index of Baker et al. (2020), 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. Realizing that the information contained in intraday data leads to more precise estimates and forecasts of daily return volatility (McAleer and Medeiros, 2008), we contribute to research on gold-returns volatility by forecasting the realized variance (RV) of gold returns, computed from 5-minute-interval intraday data, by employing a modified version of the popular heterogeneous autoregressive (HAR) model introduced by Corsi (2009). Specifically, we extend the basic HAR-RV model to incorporate information on daily EMV due to infectious diseases (EMVID) and examine its predictive power over the period 4th January 1996 to 14th May 2020. The period of the analysis incorporates various market phases such as booms and crashes, as well as the recent coronavirus pandemic which led to a substantial disruption of global economic activity.

Baur (2012) documents an asymmetric response of gold returns to positive and negative shocks, implied by lower (higher) return volatility due to a decline (increase) in trading activity in the gold

[1] For example, the jobless claims for the week ended March 21, 2020 for the United States hit an unprecedented record high of 3.28 million.

market. Given this, in the wake of heightened uncertainties due to infectious diseases and other factors, we expect a positive relationship between EMVID and gold-returns RV.

We organize the remainder of our paper as follows: Section 2 outlines the data and the methodology; Section 3 presents the results; Section 4 concludes.

2. Data and Methodology

2.1. Data

The data on the realized variance (RV) of gold returns is obtained directly from Risk Lab as maintained by Professor Dacheng Xiu at Booth School of Business, University of Chicago, and is available publicly for download from https://dachxiu.chicagobooth.edu/#risklab. Risk Lab collects trades at the highest frequencies available and cleans them using the prevalent national best bid and offer (NBBO) that is available up to every second. The estimation of the RV is based on Xiu (2010) and is derived using quasi-maximum likelihood estimates (QMLE) of volatility based on moving-average models MA(q), using non-zero returns of transaction prices sampled up to the highest frequency available, for days with at least 12 observations. The q is selected using the Akaike information criterion (AIC). We employ RV estimates based on 5-minute subsampled returns of COMEX gold futures.

The daily measure of uncertainty due to infectious diseases (EMVID) is publicly available from http://policyuncertainty.com/infectious_EMV.html. Developed by Baker et al. (2020), it is a newspaper-based infectious disease EMV tracker, available at the daily frequency from January 1985. To construct the EMVID, Baker et al. (2020) specify four sets of terms, 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 in 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 EMVID articles to total EMV articles. Based on the data availability of the two variables under consideration, our analysis covers the sample period from 4th January 1996 to 14th May 2020. This period includes various market states such as the global financial crisis of 2008-2009, yet more importantly, it also contains economic anxiety at the onset of the recent pandemic caused by COVID-19. At the end of the paper (Appendix), Figure A1 plots the data of these two variables, while basic statistics are given in Table A1.

2.2. Methodology: Heterogeneous Autoregressive Realized Variance (HAR-RV) Model

For the in-sample and out-of-sample predictability analyses, we use a variant of the widely studied HAR-RV model of Corsi (2009). While the HAR-RV model has a simple structure, it can capture, in a satisfactory way, important properties of the realized variance of gold returns, such as long memory (Gil-Alana et al., 2015), and multi-scaling behavior (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 the index h denotes h-days-ahead realized variance, with h = 1, 5, and 22 in our context. In addition, $RV_{w,t}$ is the average RV from day $t-5$ to day $t-1$, while $RV_{m,t}$ denotes the average RV from day $t-22$ to day $t-6$. When we add the EMVID to the benchmark HAR-RV model, we obtain the following extended HAR-RV model:

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

3. Empirical Results

Campbell (2008) points out that the ultimate test of any predictive model (in terms of the econometric methodologies and predictors employed) is in its out-of-sample performance. Given this, our focus is a forecasting exercise from an out-of-sample perspective. However, for the sake of completeness, in Table A2 (Appendix), we provide the full-sample estimation results for Eq. (2) for h = 1, 5, and 22. In line with the notion that gold is a traditional safe haven for investors during periods of uncertainty, we find that EMVID increases RV in a statistically significant manner (at the highest level of significance) across the three forecasting horizons.[2]

Next, we turn our attention to the primary objective of our research, i.e., the role of EMVID in forecasting the RV of gold returns. To study the out-of-sample predictability of RV, we consider a recursive estimation approach over the out-of-sample period, which covers the period 28th October 1999 to 14th May 2020. To determine the out-of-sample period, we first conduct the multiple structural break test of Bai and Perron (2003) on the HAR-RV model, and detect the following breaks: 31st March 2006 for the h = 1 and h = 5; and, 28th October 1999, 27th September 2001, 18th August 2007, and 18th October 2008 for h = 22.[3] While most of the break dates are observed during or at the onset of crises (such as the 9/11 attacks, and the recent global financial crisis), the breakpoint in 1999 is associated with the endpoint of a bearish phase in the gold market associated with the funding of new private mines, which had an adverse impact on the gold price due to them being financed by selling production forward.[4] Given that the earliest breakpoint occurred on 28th October 1999, we start our recursive estimation from this point onwards to compute the root mean squared forecast errors (RMSFEs) from the benchmark HAR-RV model and its extension based on EMVID under h =1, 5, and 22. We then use the MSE-F test of

[2] Given that daily gold price data stretches back to 1968 (from the FRED database of the Federal Reserve Bank of St. Louis) and the EMDIV is available from 1985, we also analyse the relationship between conditional gold-returns volatility, derived from an exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model (which has the best-fit among alternative GARCH models), and found the infectious-diseases-related uncertainty to increase gold-returns volatility significantly at the 5% level over the period 3rd January, 1985 to 14th May, 2020. Moreover, using Gold VIX (also available from the FRED database) between 3rd June, 2008 and 14th May, 2020, and relating it to EMVID, also produces a positive relationship at the highest level of significance. These results confirm that, just like the realized variance of gold returns, both conditional and implied volatilities are also positively impacted by EMVID. Complete details of these results are available upon request from the authors.

[3] The break dates for Eq. (2) under h=22, were exactly the same as under Eq. (1), but for h=1 and h=5, the break points were at 29/03/2006 and 30/03/2006 respectively.

[4] See the discussion at: https://www.allangray.co.za/latest-insights/markets-and-economy/gold-a-history-of-its-price/.

McCracken (2007) to compare the forecast accuracy of the augmented version of the HAR-RV model with the nested benchmark, i.e., the basic HAR-RV model in Eq. (1), which does not include the EMVID index.

Understandably, because our focus is on forecasting, a better performing model is one with a lower value of the RMSFE. In Table 1, we report the out-of-sample forecasting gains from an extended version of the HAR-RV model ($RMSFE_1$) relative to the benchmark model ($RMSFE_0$). Forecasting gains (FG) are computed as:

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

where $RMSFE_0$ and $RMSFE_1$ are the RMSFEs of the benchmark HAR-RV model the extended HAR-RV model, respectively. Given the formulation in Eq. (3), the gain (loss), in percentages, is indicated by a positive (negative) entry in the table. As can be seen from Panel A of Table 1, the FGs for all three forecasting horizons are positive, with the highest gain of 0.24% observed at h=22, followed by 0.17% and 0.13% at h=1 and h=5 respectively. This essentially implies that using the information content of the EMVID index, an econometrician can obtain forecasting gains in terms of the metric of RMSFEs associated with the forecast accuracy of the RV of gold returns relative to the benchmark HAR-RV model (which does not contain this index associated with uncertainties emanating from infectious diseases), by 0.17%, 0.13%, and 0.24% at one-day-, one-week-, and one-month-ahead. More importantly, the forecasting gains from the augmented HAR-RV model, i.e., the model with EMVID, statistically outperform the benchmark model, given that the MSE-F statistic is significant at the 1% level.[5] In other words, uncertainty due to infectious diseases contains valuable information for forecasting the future path of the realized variance of gold returns.

To highlight the role of the EMVID index specifically during the outbreak of the COVID-19 period in forecasting gold RV, we repeat our analysis by considering an out-of-sample period, 2nd January 2020 to 14th May 2020, using an in-sample period of 4th January 1996 to 31st December 2019. The results are summarized in Panel B of Table 1. They show that the FGs for all three forecasting horizons are again positive, with the highest gain of 5.53% observed at h=22, followed by 3.74% and 3.05% at h=1 and h=5, respectively.[6] Clearly, these FGs are higher than those reported in Panel A, where we analyze an extended out-of-sample period (28th October 1999 to 14th May 2020) and highlight the importance of the gain in the information contained in the EMVID index following the outbreak of the Coronavirus.[7] Similar to the results reported in Panel A, the

[5] The critical values at 10%, 5% and 1% are 0.6160, 1.5180, and 3.9510 respectively, and are derived from Table 4 of McCracken (2007, p.732).

[6] When we analyse realized volatility instead of realized variance, using the square root of the estimate of RV, the same forecasting experiment produces relatively higher gains than those reported in Panel B of Table 1. Specifically, FGs at h=1, 5 and 22 are 5.79%, 4.60% and 9.08% respectively, with the corresponding MSE-F statistic being significant at the 1% level.

[7] In order to study this point in more detail, we conduct the analysis by restricting our period of analysis to 31st of December, 2019, i.e., excluding the COVID-19 outbreak episode. The resulting FGs at h = 1, 5, and 22 are 0.03%, 0.04% and 0.02% respectively. These gains are indeed smaller than those obtained in Table 1 when we include the COVID-19 period, which is understandable given the sharp increase in the EMVID index from 2020; but they are

forecasting gains from the augmented HAR-RV model statistically outperform the benchmark model, given that the MSE-F statistic is significant at the 1% level.[8]

Table 1. Out-of-Sample Forecasting Gains

Horizon	$RMSFE_0$	$RMSFE_1$	FG
Panel A: Out-of-Sample Period: 28th October, 1999 to 14th, May, 2020			
h=1	0.0584	0.0583	0.1715***
h=5	0.0761	0.0760	0.1316***
h=22	0.0850	0.0848	0.2358***
Panel B: Out-of-Sample Period: 2nd January, 2020 to 14th, May, 2020			
h=1	0.0826	0.0796	3.7378***
h=5	0.1002	0.0972	3.0522***
h=22	0.1287	0.1220	5.5287***
Panel C: Out-of-Sample Period: 13th March, 2020 to 14th, May, 2020			
h=1	0.0815	0.0760	7.1929***
h=5	0.0900	0.0832	8.2027***
h=22	0.1461	0.1466	-0.3507

Note: Entries correspond to forecasting gains, i.e., $FG = \left(\frac{RMSFE_0}{RMSFE_1} - 1\right) \times 100$, where $RMSFE_0$ and $RMSFE_1$ are root mean squared forecast errors (MSFEs) of the benchmark HAR-RV model (Model 1): $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \varepsilon_{t+h}$, and its extended version (Model 2): $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta EMVID_t + \varepsilon_{t+h}$; RV is the daily realized variance estimate of gold returns; EMVID is the newspaper-based uncertainty index due to infectious diseases; the in-sample period in Panels A, B and C are respectively: 4th January, 1996 to 28th October, 1999, 4th January, 1996 to 31st December, 2019, and 2nd January, 2020 to 12th March, 2020; *** indicates significance of the MSE-F test statistic at the 1% level.

Finally, we conduct an out-of-sample forecasting exercise over the period 2nd January 2020 to 14th May 2020, which basically corresponds to the period of COVID-19 exclusively in our case. This COVID-19 period involves 80 observations and is not long enough to conduct a robust forecasting exercise, especially at the one-month-ahead forecasting horizon. Keeping this in mind, we conduct

statistically significant. All these FGs are still significant at the 1% level based on the MSE-F test, and hence, point to gains in forecasting of the gold-returns RV stemming from the EMVID index.

[8] The critical values at the 10%, 5% and 1% levels are 2.2100, 3.2700, and 5.9020 respectively (see Table 4 of McCracken (2007, p.732)).

an out-of-sample forecasting experiment by splitting the 80 observations into two equal parts of 40 observations each to comprise our in- and out-of-sample periods. The results are reported in Panel C of Table 1 and show FGs of 7.29% and 8.20% at h=1 and h=5, but a loss of 0.35% at h=22. Importantly, the MSE-F statistics for one-day- and one-week-ahead forecasts continue to be statistically significant at the 1% level,[9] even with such a short out-of-sample period. Such evidence is particularly important for investors during the current period of unprecedented levels of uncertainty resulting from the outbreak of COVID-19. This is because unlike regular downturns starting with a moderate yet accelerating decline in economic activity, the current global spread of this novel virus posed a sudden shockwave in the global economy and global financial markets, while investors and policymakers were unprepared to effectively manage the effects of this shock (see Fetzer et al., 2020).

Overall, our findings extend the previous literature showing that risks associated with geopolitical, economic, and financial events have the power to forecast the volatility of gold returns by providing the first empirical evidence on the forecasting power of the uncertainty associated with epidemic and pandemic diseases for the realized variance of gold returns.

4. Conclusion

The role of gold as a traditional safe haven during periods of heightened uncertainty is well-established in academia as well as in the financial media. Given the recent surge in uncertainty due to the outbreak of the COVID-19 pandemic, we go beyond the previous literature on forecasting gold-returns volatility in a novel direction by exploring the predictive power of a daily newspaper-based metric of uncertainty associated with infectious diseases (EMVID). When we include the information from this index in a standard HAR-RV model, we find that the EMVID index increases gold realized variance in the in-sample exercise, while it is significantly improving the out-of-sample forecasting performance. Importantly, in order to further evaluate the role of the EMVID index in forecasting gold during the spread of the COVID-19 disease, we conduct an out-of-sample forecasting analysis that exclusively corresponds to the period of COVID-19. Again, our results point to a critical role of this index in forecasting gold RV. This is highly important for investors, financial risk managers, and policymakers as the novel virus -in contrast to regular downturns starting with a moderate yet accelerating decline in economic activity- posed a global sudden shock in economic activity and financial markets around the world.

To conclude, given the importance of accurate volatility forecasts in the pricing of derivatives as well as the computation of optimal investment positions, our findings suggest that incorporating uncertainty associated with infectious diseases in forecasting models can help improve the design of portfolios that include gold as a hedge against financial-market risks due to virus outbreaks, across various investment horizons. As part of future research, it would be interesting to extend our study to other popular safe havens such as US Treasuries,[10] the Swiss franc and Japanese yen,

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[9] The critical values at 10%, 5% and 1% levels are 0.7510, 1.5480, and 3.5840 respectively (see Table 4 of McCracken (2007, p.732)).

[10] With US Treasury securities considered a well-established safe haven, a preliminary analysis for 10-year bonds, based on data derived from the same source, shows forecasting gains for realized variance at short- and medium-runs,

and even the cryptocurrency Bitcoin, which has recently gained popularity as a hedge against financial market risks.

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but not in the long run. Details of these results are available upon request from the authors. Of course, US Treasury securities and other safe havens deserve a more detailed analysis to obtain concrete evidence of the predictability of the variance of these assets based on the EMVID index.

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APPENDIX

Table A1. Summary Statistics

	Variable	
Statistic	RV	EMVID
Mean	0.1455	0.7357
Median	0.1295	0.0000
Maximum	1.0996	77.3500
Minimum	0.0000	0.0000
Std. Dev.	0.0904	3.4972
Skewness	2.1678	11.8068
Kurtosis	13.3001	166.0404
Jarque-Bera	29879.86	6493193.00
p-value	0.0000	0.0000
Observations	5742	5742

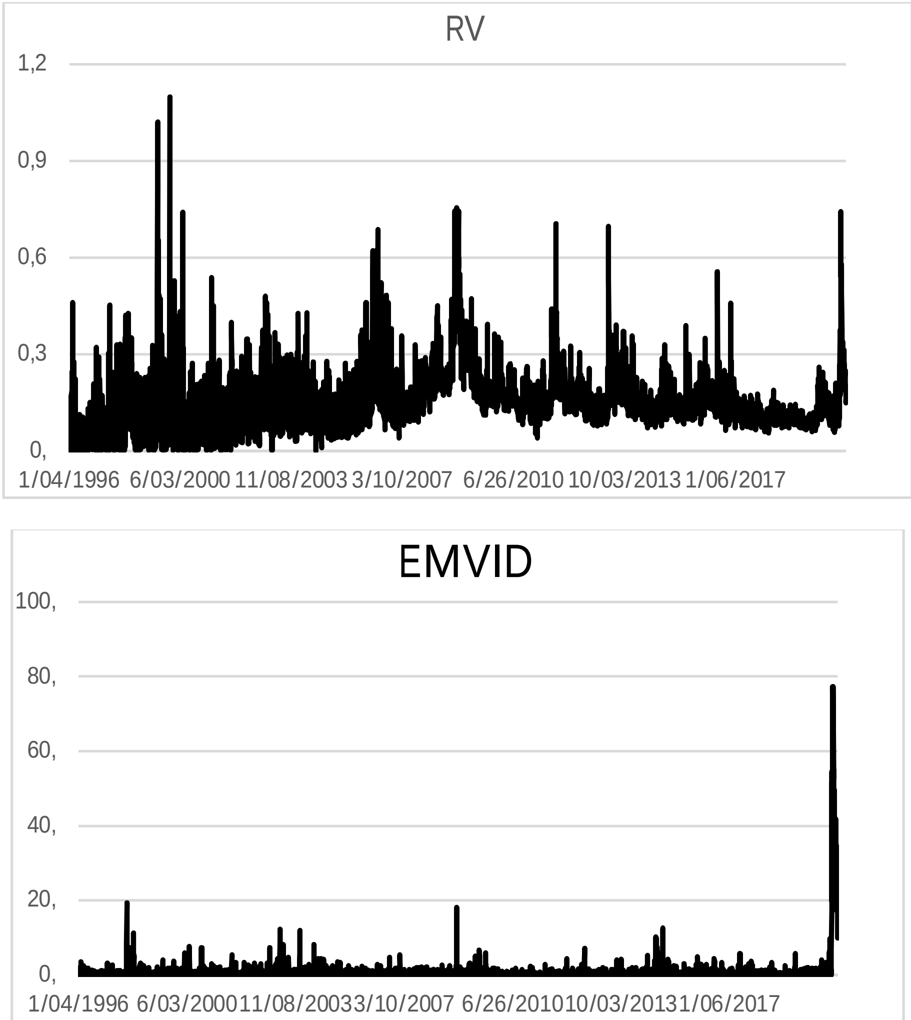
Notes: Std. Dev. stands for standard deviation; *p*-value corresponds to the null hypothesis of normality associated with the Jarque-Bera test; RV is the daily realized variance estimates of gold returns; EMVID is the newspaper-based uncertainty index due to infectious diseases.

Table A2. In-Sample Predictability Results

Horizon	β_0	β_d	β_w	β_m	θ
h=1	0.0116^{***}	0.2156^{***}	0.3800^{***}	0.3212^{***}	0.0009^{***}
h=5	0.0131^{***}	0.5242^{***}	4.2110^{***}	0.1694^{***}	0.0011^{***}
h=22	0.0039	0.2123^{***}	0.7855^{***}	20.9704^{***}	0.0016^{***}

Notes: This table presents the estimates for the full-sample: $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta EMVID_t + \varepsilon_{t+h}$; *** indicates significance at the 1% level.

Figure A1. Data Plots



Notes: RV is the daily realized variance estimates for gold; EMVID is the newspaper-based uncertainty index due to infectious diseases.