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Time Varying Spillovers of COVID-19 on the Financial Markets

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ABSTRACT

Purpose – The COVID-19 pandemic has generated exceptional response of the financial markets and exceptional increase in the volatility of asset classes. The aim of this study is to establish influence of daily ambiguity surrounding infectious disease. In particular, the purpose is to test as to how the impacts of the COVID-19 pandemic have generated volatility spillovers both onto and within traditional financial market assets.

Design/methodology/approach – In this study, the methodological approach is developed upon a time-varying robust Granger-causality methodology, which is further designed to incorporate macroeconomic variables using sentiment indices and policy uncertainty indices as additional control variables.

Findings – The analysis reveals that EMVID index has a vital role in driving both price and volatility of the asset classes being investigated. It also has a considerably varying effect on these financial assets. It is also shown that there are major differences of international response across the markets for equities, oil, gold and cryptocurrency. Furthermore, the transmission of volatility spillovers in the early Asian occurrence of the COVID-19 epidemic show that the financial markets that did not adequately identify the threat in the earlier phase of the pandemic.

Discussion – The results help both investors and policymakers in their decision-making process as it is shown that although oil and bond markets presented some early signs for the volatility transmission, it was mainly currency and in particular cryptocurrency markets with more immediate and influential effects. Furthermore, the results provide support for the increasing maturity of the cryptocurrency ecosystem. On the other hand, they also present some important outcomes for regulatory authorities and policymakers. For instance, while the currency markets demand for cash as a catalyst of volatility and oil prices and demand adapt due to worldwide economic recession, cryptocurrency market would not be expected to respond in the same way. This result has the implication that cryptocurrencies were employed as a safe-haven vehicle during the onset of this incredible event.

1. INTRODUCTION

The outburst of the COVID-19 epidemic has become one of the defining international moments of a generation, stifling economic growth and generating much in the way of social, political, behavioural and structural change. While such international response has varied substantially by region, one key area of research through which much value can be obtained surrounds the manner in which financial market response disseminated in coordination with the expected level of severity of this developing pandemic. That is, to what extent and at what specific time did volatility spillovers disseminate throughout traditional financial markets. Corbet et al. (2021) previously identified that Chinese companies based at the epicenter of the battle against COVID-19 epidemic. In this paper, we set out to establish the impact of daily ambiguity around infective disease (EMVID index) has generated volatility spillovers across traditional financial market assets, developing upon a time-varying robust Granger-causality methodology, adjusted to incorporate macroeconomic conditions and economic policy-related events.

The timing of such dynamic volatility spillovers is of particular interest. A substantial amount of research has already focused on dynamic variants of market interactions, including that of volatility, price discovery and information flows (Alexakis et al., 2021), however, much of this work has determined that initial phases of COVID-19 epidemic generated little of a substantiative effect on traditional financial assets. Some research has however identified a potentially central role for cryptocurrency as a safe place during the initial stages of the identification of financial markets as to the true extent of the severity of the COVID-19 epidemic (Adediran et al., 2020, Dutta et al., 2020, Ji et al., 2020, Chen et al., 2020, Kristoufek, 2020, Adediran et al., 2020). However, such interactions have yet to be tested when considering indices such as that relating to uncertainty relating to pandemics and infectious disease. Further, the dissemination of information and the rational underlying certain market movements is also very much of interest. Within this context, much has been made of the movements of WTI oil during the period around the incredible negative pricing issues of April 2020 (Corbet et al., 2020), or indeed, a significant number of papers that concentrate on the effects of COVID-19 on the markets for gold, currencies, bonds and equities (Adekoya et al., 2020, Ali et al., 2020, Hu et al., 2020). While time-changing responses to the crises are central to this research, it is also important to note geographical concerns. As presented in Figure 1-4, we observe the differential of response during the time intervals both shortly earlier and later the Chinese outbreak of the COVID-19 pandemic (the shaded red region represents the period of time surrounding the 1st of January 2020, representing the time of the WHO announcement of the existence of a global pandemic, and the 31st March 2020), to which much limited western interaction had been identified. It is quite clear that the response of financial markets varied substantially in a geographical context, but also, quite broadly when considering the lack of forward-looking indices such as that of the VIX and VSTOXX, incorporating option-defined volatility in both the US and Europe respectively.

Figure 1. SSEA (Shanghai Stock Exchange) response to the initial announcement of COVID-19.

Figure 2. DJIA (Dow Jones Industrial Average) response to the initial announcement of COVID-19.

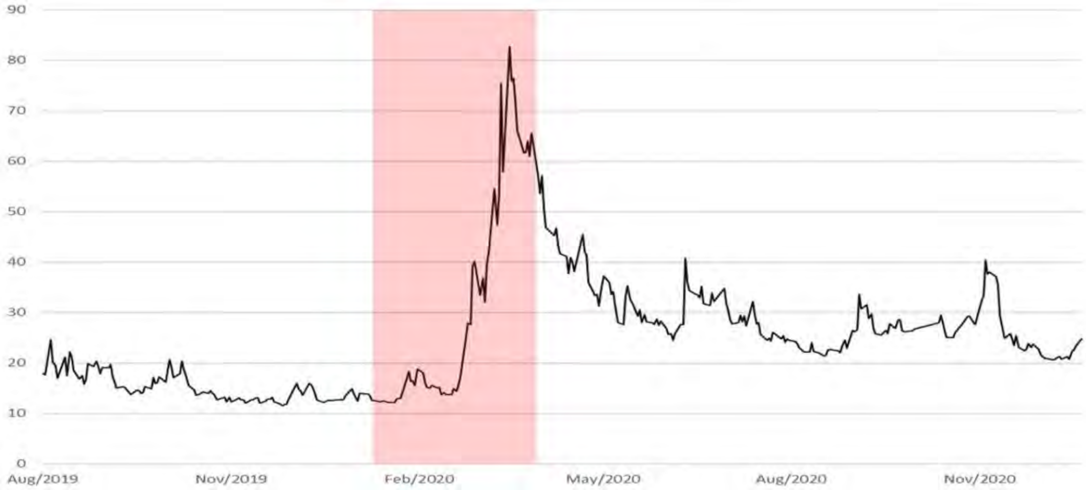


Figure 3. VIX (CBOE Volatility Index) response to the initial announcement of COVID-19.

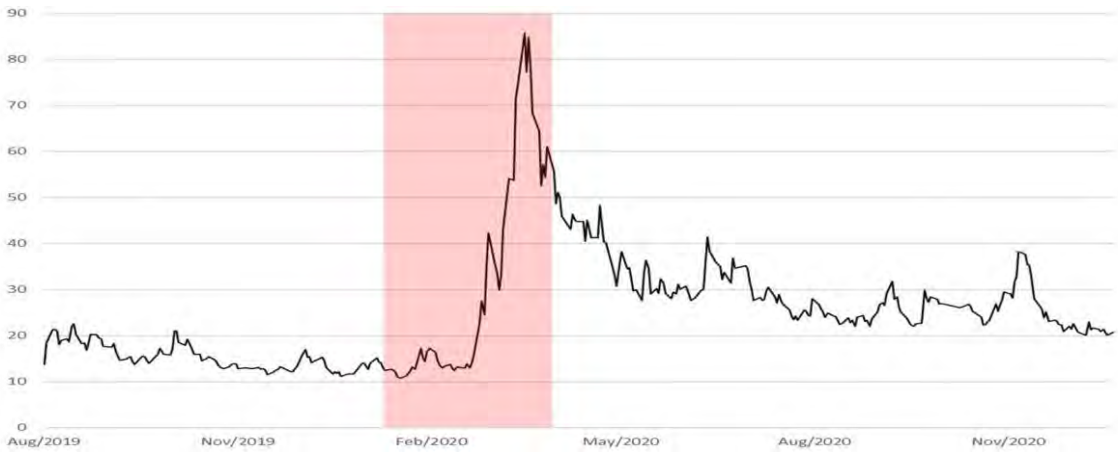


Figure 4. VSTOXX (EURO STOXX 50 Volatility Index) response to the initial announcement of COVID-19.

In this research, we establish that the EMVID index is a significant factor driving not only the price, but the volatility of the asset classes, while also possessing a varying effect on the financial assets analysed. However, this time-varying volatility interaction did not appear to be a present entirely in January 2020 during the initial WHO announcement of an international pandemic outbreak, however, generate significant effects during the spread and escalation of the pandemic to the US and Europe throughout March and April 2020. Such shocks are found to influence the markets for equities, oil, gold and cryptocurrency, where previous evidence suggested the existence of a number of hedging and diversification dynamics during the associated investor flight-to-safety due to the COVID-19 outburst. However, the transition of volatility spillovers presents evidence of financial markets that did not adequately identify the threat evidence in the early Asian outbreak of the COVID-19 contagion. It is very much of interest to note that while oil and bond markets presented some evidence of early volatility transfer, it was largely currency, and indeed cryptocurrency markets that presented the most immediate and substantiative effects. The later result, while presenting further evidence of a maturing marketplace also presents quite a worrying outcome for regulatory authorities and policymakers.

The paper is organised as follows: Section 2 presents a detailed review of the related literature. Section 3 outlines the data used in this analysis. Section 4 describes the methodology utilized followed by prediction results in Section 5. Section 6 concludes the paper.

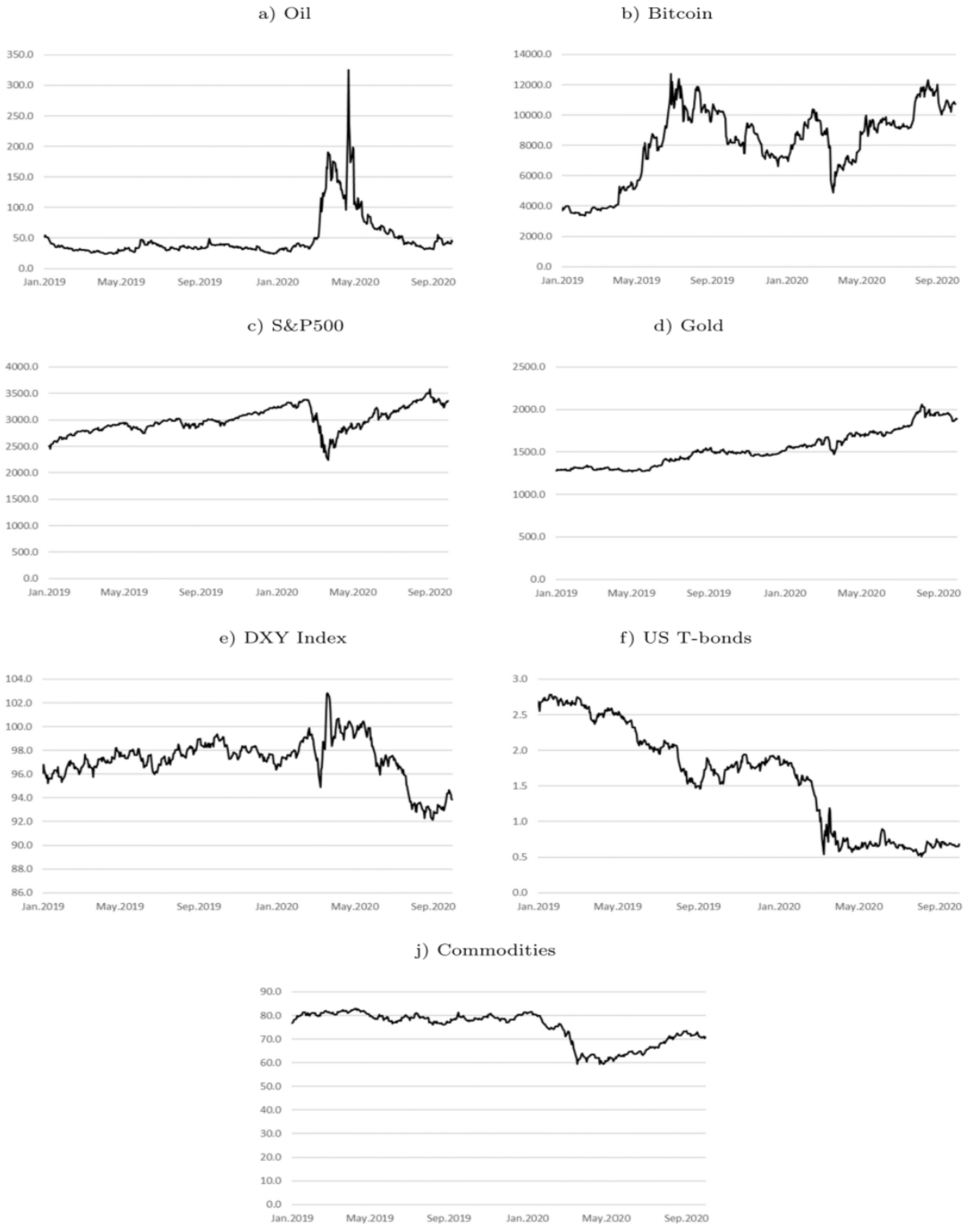
2. LITERATURE REVIEW

Our research builds upon a number of key areas of development. First, we develop on the broad variety of work that has focused on contagion between financial markets during crisis, and the spillover of financial market volatility. One of the leading pieces of research based on directional volatility spillovers was presented by Diebold and Yilmaz (2012) which focus on US financial markets between January 1999 to January 2010 and show that spillovers were most pronounced during the 2007 financial crisis. This had developed on Diebold and Yilmaz (2009), where proof of differing behaviour in the dynamics of return spillovers is identified when compared to volatility spillovers. Spillovers had also been identified to be far more likely in equity markets than bond markets (Hartmann et al., 2004). Kodres and Pritsker (2002) provide evidence that cross-market stabilization is mostly responsible for market interactions. Similar spillovers had been also identified within market liquidity dynamics (Karolyi et al., 2012). Extreme interdependencies had previously been associated between the BRIC (Brazil, Russia, India, China) markets and the US markets during the 2007 financial crisis (Aloui et al., 2011, Kocaarslan et al., 2017). Evidence of shocks generating increased correlation dynamics and spillovers were also identified throughout European stock markets (Baele, 2005, Bekaert et al., 2009), emerging markets (Bae et al., 2003, Samarakoon, 2011), Japan (Karolyi and Stulz, 1996), Asia during the financial crisis of 1997 through 1998 (Yang et al., 2003). Tiwari et al. (2020) found evidence of negative relationship structure for the return series between machine learning and carbon prices.

The outburst of the COVID-19 contagion has generated very different financial market interactions, many of which are the focus of the following research. Smales (2021) found that while monitoring for the impact of pandemic and broad macroeconomic variables, elevated Google searching volumes have had less of an impact on government bond yields because of small percentage involvement of retail depositors. Gupta et al. (2021) identified significant effects of the pandemic on US interest rates, while using intraday gold and oil data, Mensi et al. (2020) show convincing evidence of asymmetric multifractality that rises as the fractality scale grows. Ramelli and Wagner (2020) identified that international firms, especially those more involved in trade with China, under-performed. When focusing on elements of firm structure, Mirza et al. (2020) found that creditworthiness of all firms weakens during COVID-19 in the European Union. (Corbet et al., 2020) identified that those unlucky to share brand characteristics with the name of pandemic suffered substantial abnormal impacts. Further, Wang et al. (2020) showed that the HAR-RV-VIX model exhibited higher prediction ability during the turmoil period. Salisu et al. (2020) utilised an asymmetric VARMA-GARCH model, to analyse oil and gold hedging during the pandemic, identifying that gold behaved as a important safe investment against fluctuations in oil prices associated with pandemic-driven fear. Adekoya and Oliyide (2020) analyzed the impact of disease on the connectedness between the markets. Other sectors and phenomena relating to the pandemic analysed included that of the negative WTI oil price event (Corbet et al., 2020), the impacts of spillovers upon the BRICS (McIver and Kang, 2020) and the effects of macroeconomic factors (Hu et al., 2020).

3. Data

Our data set includes daily return and volatility of a range of financial assets, namely, stock price index of S&P 500, gold, Brent oil, Bitcoin, DXY index, Bloomberg commodity index (BCOM) and ten-years U.S. treasury bond yield over the periods of September 1, 2019 to September 30, 2020. Daily returns are computed as: $r_{t,j} = \ln P_t - \ln P_{t-1}) \times 100$ where P_t is the daily closing value for financial asset j. Following Forsberg and Ghysels (2007) and Antonakakis and Filis (2013), we define the volatility of the financial asset j as the absolute return: $V_{t,j} = |\ln P_t - \ln P_{t-1}| \times 100$. Figures 2 and 3 plot the daily series of the return and volatility of the financial assets.



Note: The above price series represent the use of the Generic 1st ’CL’ Future, XBTUSD BGN Currency, the S&P500 Index, Gold Spot ($/Oz), the DXY US dollar index, the US Generic Govt 10 Year and the Bloomberg Commodity Index respectively.

Figure 5. Prices of the selected series, 2019-2020

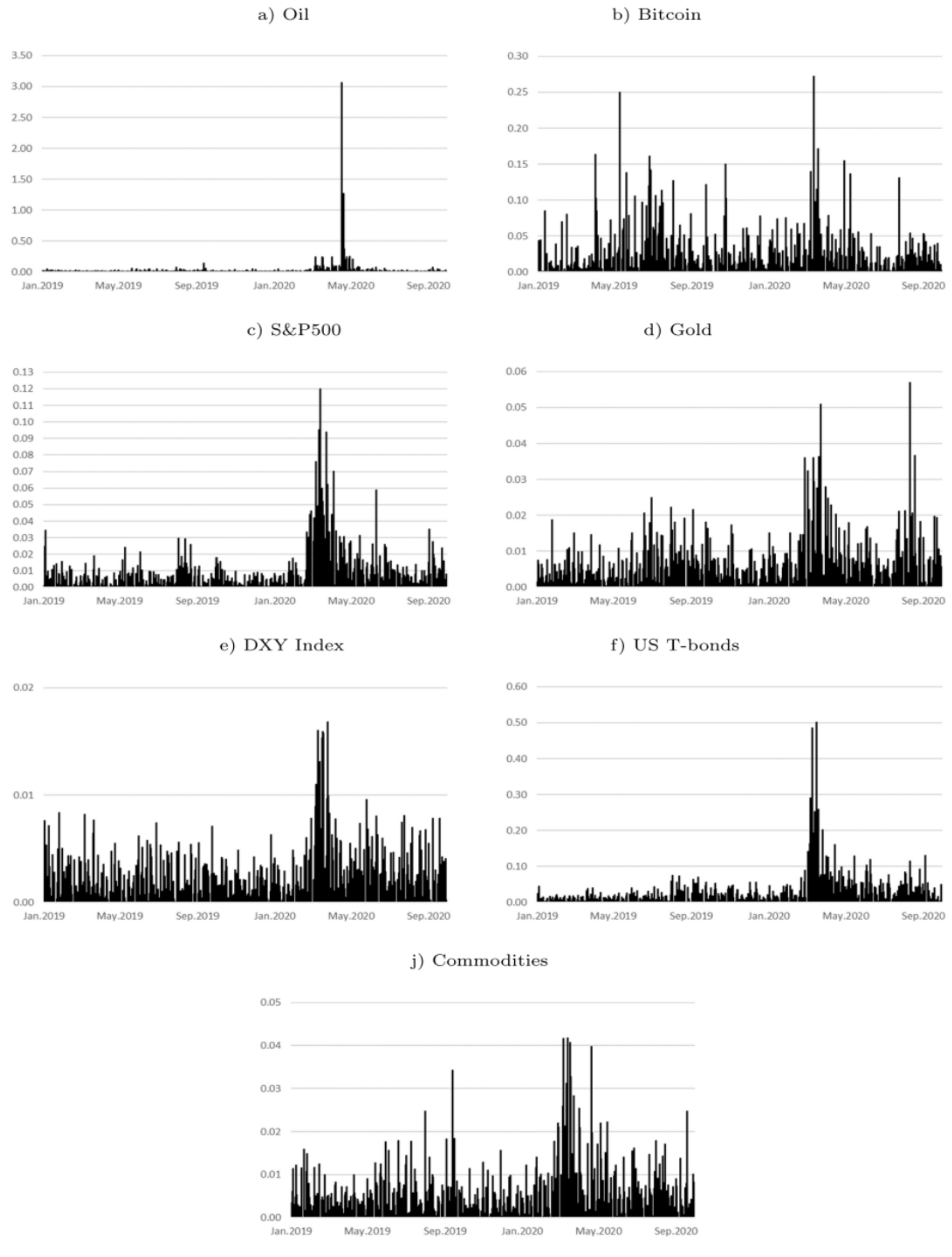


Figure 6. Price volatility of the selected series, 2019-2020

To examine the effects of COVID-19 contagion on financial assets, daily measure of uncertainty due to infectious diseases (EMVID) is used (Please see Baker et al. (2020) for the details of the index construction). Figure 4 shows that the index increased sharply at the beginning of March and reached its peak around early April due to the COVID-19's quick contagious nature.

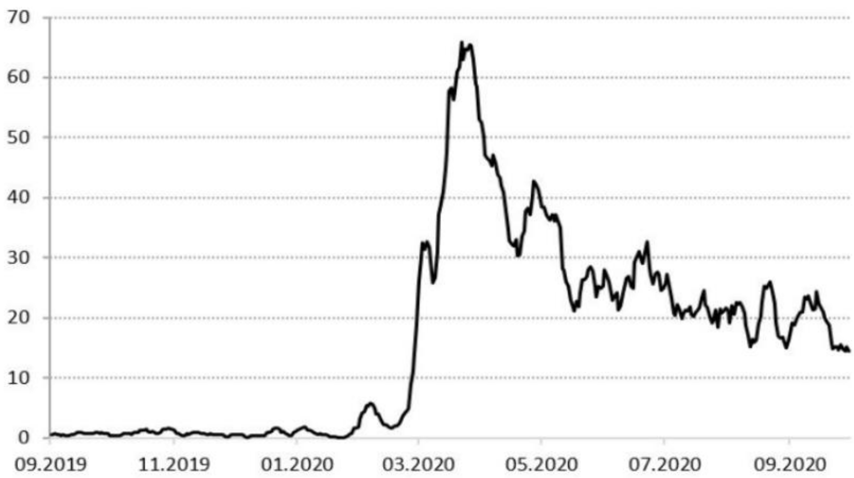


Figure 7. Daily infectious disease equity market volatility tracker (1-week moving average)

We also consider that developments in macroeconomic conditions and economic policy related events might contaminate the relationship between corresponding asset class j and COVID-19 pandemic index. We use the US Federal Reserve Bank of San Francisco daily news economic sentiment index (ESI) and US economic policy uncertainty (EPU) index as an additional control variable. All data are downloaded from Bloomberg terminal.

4. METHODOLOGY

In this paper we follow the methodology introduced by Rossi and Wang (2019) to the literature. Their model brings important improvements over the linear model. One of the main advantages is that test results are more robust in case of the instabilities compared to the conventional test results. Another advantage is that the proposed test helps to identify the periods where Granger-causality is observed. In this paper, we employ this methodology to analyze the time-varying causal dynamics between EMVID index and financial variables during the COVID-19 period and obtain more promising results compared to the conventional Granger causality method. Specifically , the following reduced-form VAR with time-varying parameters is utilized:

$$\begin{aligned} B_t(L)y_t &= u_t \\ B_t(L) &= I - B_{1,t}L - B_{2,t}L^2 - \cdots - B_{q,t}L^q \\ u_t &\overset{i.i.d}{\sim} (O,\Sigma) \end{aligned} \tag{1}$$

where x_t=[$x_{1,t}$, x,…, $x_{n,t}$]' is an m×1 vector, and $B_{i,t}$, i=1,…,q, is m×m time-varying coefficient matrice. In this paper, x consist of ESI, EPU, EMVID index and return (also volatility) of the asset i where i=oil, bitcoin, S&P 500, gold, DXY index, BCOM and 10-years US sovereign bond yield.

Furthermore, a straight-forward multi-step VAR-LP is implemented to explore the prediction power of EMVID index. By repeating Eq. (1), y_{t+k} can be forecasted onto the linear space generated by $\left(x_{t-1}, x_{t-2}, \dots, x_{t-q}\right)'$ make use of the subsequent equation:

$$x_{t+\mathrm{k}} = \Phi_{1,t}x_{t-1} + \Phi_{2,t}x_{t-2} + \cdots + \Phi_{p,t}x_{t-p} + \epsilon_{t+\mathrm{k}} \tag{2}$$

where $\Phi_{i,t}, i = 1, \dots, p$ are functions of $B_{i,t}, i = 1, \dots, q$ in Eq.(1), and ϵ_{t+k} is a moving average of the error term u_t from time t to t+k. Hence we observe that Eq.(1) is a particular case of Eq.(2) when k=0. Thus, Eq.(2) is used in the remaining part of the analysis.

Assume that θ_t is a proper subset of the vector $\left(\Phi_{1,t}, \Phi_{2,t}, \dots, \Phi_{p,t}\right)$. We then check H_0 hypothesis that EMVID index does not Granger cause the return (also volatility) of financial variable j=oil, bitcoin, S&P 500, gold, DXY index, BCOM and 10-years US sovereign bond yield where the null hypothesis is that:

$$H_0\colon \theta_t = 0, \text{ for each t} = 1,2, \dots, \mathrm{T}. \tag{3}$$

By following a similar approach as in Rossi (2005), three different test statistics that are (MeanW), Nyblom (Nybolm) and Quandt Likelihood Ratio (SupLR) tests are presented. Considering the Schwarz Information Criterion (BIC), lag length for the VAR model is found to be one and the standard trimming parameter is chosen to be 0.10 in order not to lose too much data.

5. Results

Table 1 presents the results from reduced-form TVP-VAR model in the top panel. From the first column of Table 1 we observe that constant parameter Granger causality test cannot find causality between EMVID index and asset returns. The null of no-Granger causality from the EMVID index to asset return is rejected with a significance level of 5%. In contrast, regardless of the test-statistic considered (MeanW, Nyblom, SupLR), there exists a consensus among findings affirming that the EMVID index Granger cause the returns for sample assets when instabilities are considered. That is to say, H_0 hypothesis of the robust Granger causality test can be rejected at 5% significance level. Similarly, test results reported in the bottom panel of Table 1 show that the EMVID index is also significant factor for driving the volatility of the asset classes. The results also hold independent of the test statistic and they are also verified by conventional Granger causality test with the exception of oil price volatility. Therefore, it is observed that the outlook of the EMVID index is a crucial element of anticipating the volatility of the financial assets.

Table 1. TVP Granger causality tests results

	χ^2_q	MeanW	Nyblom	SupLR
RETURN				
Oil	2.76	64.11	3.49	344.26
	(0.430)	(0.000)	(0.022)	(0.000)
Bitcoin	1.43	20.34	11.84	135.83
	(0.699)	(0.000)	(0.000)	(0.000)
S&P 500	5.79	48.31	41.65	516.60
	(0.215)	(0.000)	(0.000)	(0.000)
Gold	0.45	18.76	4.15	295.09
	(0.503)	(0.000)	(0.000)	(0.000)
DXY Index	0.94	91.30	97.91	479.48
	(0.331)	(0.000)	(0.000)	(0.000)
US Treasury Bond 10Y	3.87	48.01	53.36	589.08
	(0.276)	(0.000)	(0.000)	(0.000)
Commodity	1.39	147.25	55.45	857.76
	(0.708)	(0.000)	(0.000)	(0.000)
VOLATILITY				
Oil	5.88	192.63	42.45	403.20
	(0.117)	(0.000)	(0.000)	(0.000)
Bitcoin	11.63	122.53	35.48	785.06
	(0.009)	(0.000)	(0.000)	(0.000)
S&P 500	11.73	306.85	96.69	2364.76
	(0.003)	(0.000)	(0.000)	(0.000)
Gold	17.87	155.65	73.67	1259.04
	(0.001)	(0.000)	(0.000)	(0.000)
DXY Index	28.83	203.41	191.37	999.21
	(0.000)	(0.000)	(0.000)	(0.000)
US Treasury Bond 10Y	20.71	172.69	76.99	773.13
	(0.001)	(0.000)	(0.000)	(0.000)
Commodity	34.68	275.39	314.29	2200.28
	(0.000)	(0.000)	(0.000)	(0.000)

Furthermore, Table 2 presents the results for 3, 6, and 9-months horizons coming from direct multi-step VAR-LP forecasting. We can observe from the top panel in Table 2 that null hypothesis can be rejected at 5% significance level. This result also shows that EMVID index contains valuable information for the prediction of financial returns. The above-mentioned results do not change with the test statistic, the financial asset class of interest as well as the forecast horizons. Table 2 shows results associated with volatility in the bottom panel of the table which again confirm the significance of the EMVID index. In addition, the lower panel of Table 2 shows the statistics associated with the volatility, which again confirm the significance of the EMVID index in the VAR-LP forecasting setting. Put differently, the in-sample informative nature of the EMVID index for asset volatility is supported by statistically significant out-of-sample predictability indicating that the realization of the EMVID index can be used to predict the course of volatility in the financial markets when instability and the time-varying nature are taken into consideration.

Table 2. Robust Granger-causality tests results in the direct multi-step VAR-LP forecasting framework

					RETURN				
		h=3			h=6			h=9	
	MeanW	Nyblom	SupLR	MeanW	Nyblom	SupLR	MeanW	Nyblom	SupLR
Oil	65.78	22.72	401.86	80.49	8.67	1130.06	72.23	12.34	374.43
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bitcoin	34.84	20.47	390.36	22.19	2.94	227.27	35.63	25.02	1497.94
	(0.000)	(0.000)	(0.000)	(0.000)	(0.038)	(0.000)	(0.000)	(0.000)	(0.000)
S&P 500	19.36	6.24	252.16	56.41	18.53	699.04	113.97	71.26	673.41
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gold	24.23	18.32	281.54	22.25	2.82	455.14	64.20	46.56	463.65
	(0.000)	(0.000)	(0.000)	(0.000)	(0.043)	(0.000)	(0.000)	(0.000)	(0.000)
DXY Index	45.24	70.58	361.18	34.58	11.76	274.79	37.42	8.13	353.86
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
US Treasury Bond 10Y	71.16	72.53	934.25	21.07	14.36	338.25	51.98	141.48	640.46
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Commodity	105.66	112.63	569.04	91.23	47.44	1714.93	63.78	30.51	2156.23
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
					VOLATILITY				
		h=3			h=6			h=9	
	MeanW	Nyblom	SupLR	MeanW	Nyblom	SupLR	MeanW	Nyblom	SupLR
Oil	74.53	21.26	179.74	208.25	44.66	659.28	129.72	54.59	651.69
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bitcoin	85.96	24.16	454.78	84.84	49.45	730.50	104.36	168.49	1442.02
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S&P 500	178.34	69.74	1802.45	173.89	252.32	3155.95	193.93	142.38	2609.33
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gold	157.89	156.88	2233.57	87.07	109.30	670.29	122.03	76.98	1528.15
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DXY Index	171.13	163.84	1590.33	213.86	917.70	2703.32	136.75	171.22	1216.40
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
US Treasury Bond 10Y	164.42	28.81	1519.86	153.01	83.16	1536.38	229.03	114.93	1512.66
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Commodity	148.92	376.70	866.71	161.07	43.05	2464.48	112.77	314.20	1762.37
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

In addition to the results explained above, we present the whole sequence of the Wald statistics across time in Figure 5 which gives more information on when the Granger-causality occurs. We also observe that Wald test statistic for oil price return is above the threshold level for most of the analysis period and obtains its highest value in March. A substantial negative global demand shock from the proliferation of COVID-19 globally is likely to result in a large hit to global discretionary demand which in turn led to oil prices down significantly. Furthermore, the failure of oil producers to agree on productions cuts has led to a price war which in turn caused oil prices to plunge down nearly US$30/barrel. Similar conclusions are also valid for overall commodity markets since mitigation measures have significantly reduced transportation which resulted in unprecedented disruptions to supply chains, while weaker economic growth led to reduced overall commodity demand further. When we consider the estimation outcomes for Bitcoin returns, it is observed that significant time-varying Granger causality results are apparent both around the mid of the March and early September. As pointed out by Corbet et al. (2020) and Conlon et al. (2020), the safe heaven nature of the cryptocurrencies can be deteriorated during the serious financial and economic disruption. Hence, our results confirm their findings that cryptocurrencies have traded more in line with risky assets since early-March rather than performing like safe heaven. In addition, the Granger-causality relationship between bitcoin returns and the EMVID index seems to be strengthened again around early September periods because of the lingering concerns from the second wave of COVID-19 infections.

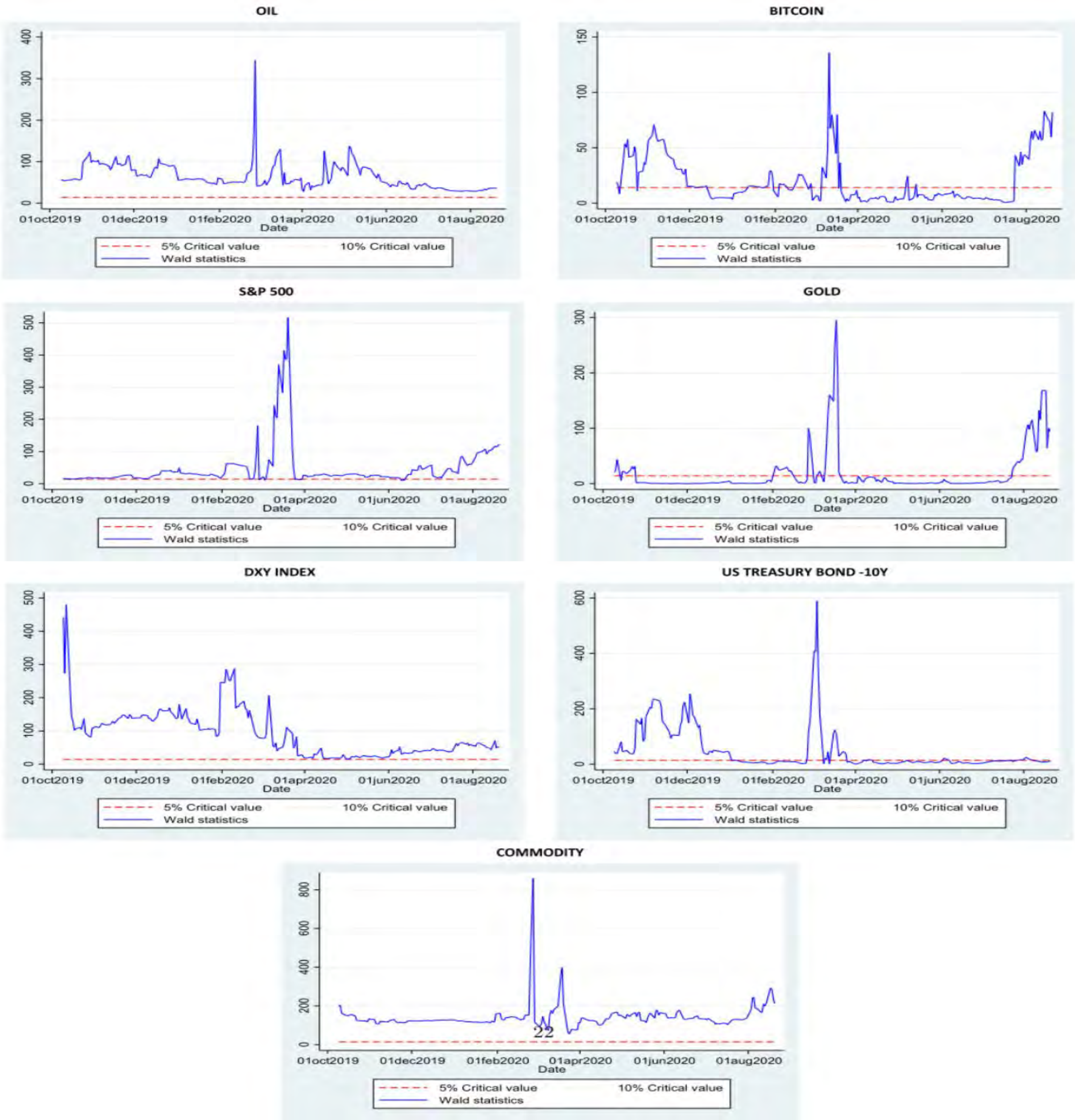


Figure 8. TVP-Wald statistics robust Granger-causality tests for asset returns

The relationship between the pandemic and equity market represents similar dynamics. Elevated numbers of coronavirus cases have impacted markets across the globe, making investors more pessimistic about the speed of global economic recovery from the pandemic, which leading to global sell-off in equity markets. Our results validate the findings of Sharif et al. (2020), which identify a substantial coherence at the end of March because of the combined effect of the sharp drop in oil prices and COVID-19 fears. Furthermore, using a Wavelet coherence analysis, they show that there is an anti-cyclic effect between COVID-19 and US stock index where COVID-19 is leading. In Figure 4, our results also provide evidence for the flight-to-safety trend from pandemic resulting turmoil to gold and bond markets (Baur and Lucey, 2010). At the same time, many Central Banks start purchasing government bonds in the secondary market and offer repo transactions to financial institutions to moderate the abnormal volatility and to increase the liquidity in the financial markets. In this regard, quantitative easing policies also increase the demand for government bonds and suppress the bond yield.

A closer look at Figure 5 also reveals that the effect of COVID-19 on DXY index is evident around early January, coinciding with the start of the COVID-19 pandemic. The reason is that the meltdown in global markets due to the global recession fears has led to a huge demand for cash (Bouri et al., 2021). To further analyze the relation between volatility of the selected financial variables and COVID-19, Figure 6 again reports the time-varying Wald statistics for each financial asset. It can be observed that the effect of COVID-19 is mostly influential over the whole sample periods and for all asset classes, although its impact is more prominent around the mid of March. Hence, our results provide evidence for sharp and unusual volatility impacts that have been produced within the COVID-19 period.

Overall, our findings suggest that the COVID-19 pandemic is causing the unprecedented response of the financial markets and exceptional increase in the volatility of asset classes. One policy implication of these results could be the necessity of strong commitment to appropriate macroeconomic policies and prudential tools to mitigate the effects of volatility in the financial market, which would improve investor confidence during times of elevated uncertainty. In other words, analysing the effect of the COVID-19 on financial markets can yield valuable information for investors and policymakers for the future deteriorating circumstances which may appear as a result of second wave of pandemics. From the asset management perspective, our results show the strong short-term impact of COVID-19 on the financial markets. Hence, global investors could use our findings to diversify/hedge their portfolios in periods of heightened uncertainty.

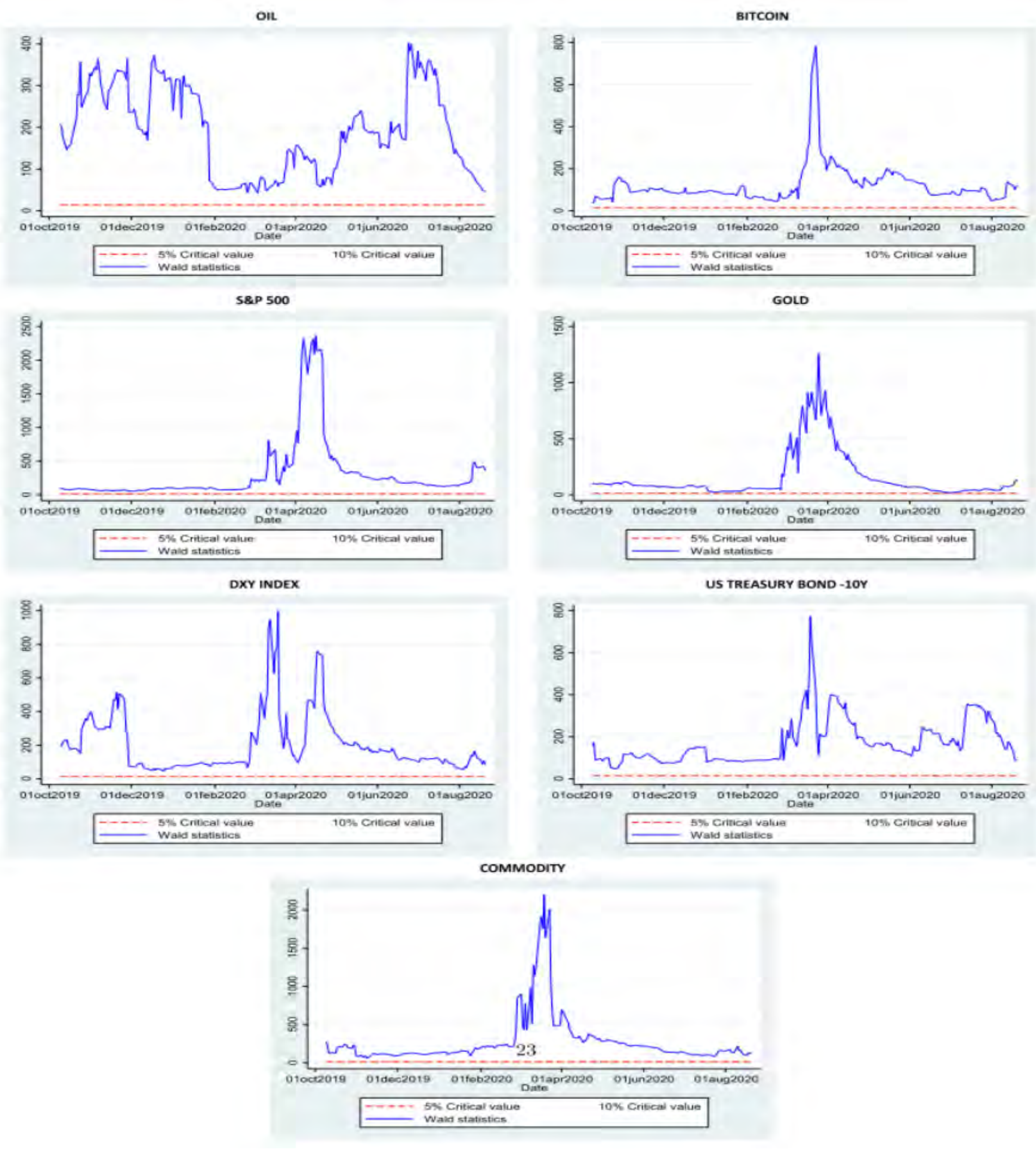


Figure 9. TVP-Wald statistics robust Granger-causality tests results for asset volatilities

6. CONCLUSION

In this research, we set out to establish the influence of daily uncertainty surrounding infectious disease as introduced by Baker et al. (2020), to specifically test as to how the influences of the pandemic have generated spillovers onto traditional financial market assets. To complete such a task, we develop upon a time-varying robust Granger-causality methodology, which is further designed to incorporate macroeconomic variables through the use of sentiment indices and policy uncertainty indices as additional control variables.

We establish that under TVP-VAR methodology , that developed EMVID index Granger causes the returns for sample assets when instabilities are accounted for, while also finding also that it is a significant factor for driving the volatility of the asset classes. While evidence suggest that the EMVID index is a crucial element of anticipating the volatility of the financial assets, evidence suggest that it possessed a substantially varying effect on the financial assets analysed, and for the most part, did not appear to be a substantial driver. It is also shown that the EMVID index can be used to predict the course of volatility in the financial markets. Such shocks are found to influence the markets for equities, oil, gold, and cryptocurrency, where previous evidence suggested the existence of a number of hedging and diversification dynamics during the associated investor's move to safe assets. However, the transition of volatility spillovers presents evidence of financial markets that did not identify the threat evidence in the initial Asian burst of the disease. The only market that appears to have almost immediately responded to the January 2020 phased of the pandemic was that of the DXY index, evidenced through broad identification that recession fears would lead to a substantial increased demand for cash, particularly due to the negative rate environment that exists in many countries towards savings and bonds. When investors did eventually identify the deep-rooted economic consequences of the pandemic as identified through significant outbreak dates in the US and Europe, markets respond almost immediately.

While the existence of volatility spillovers, is in itself, not explicitly novel, however, the time-varying nature of these volatility spillovers are very much of interest. The broad international response and spillover of volatility based on the COVID-19 pandemic was significantly slower than that presented in currency markets, indicating that traders, while identifying that COVID-19 presented many international issues, they underestimated the scale to which this event would influence daily life around the globe. It would be of interest to traders and policymakers to note that while oil and bond markets presented some evidence of early volatility transfer, it was currency, and indeed cryptocurrency markets that presented the most immediate and substantiative effects. The later result, while presenting further evidence of maturing markets also presents quite a worrying outcome for regulatory authorities and policymakers, with evidence suggesting that while currency markets identified demand for cash as a propellant of volatility, and oil demand and pricing adjusted due to expectations of broad economic slowdown due to COVID-19, however, cryptocurrency would not be expected to react in the same manner. Such result presents evidence that cryptocurrency was used as a safe-haven vehicle during the onset of this incredible 'black swan' event.

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