Timing Matters: Bitcoin Returns, Public Attention to COVID-19, and Individualism

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Abstract

The pandemic evolution and people’s concern over it have an impact on the Bitcoin market, while the extent of individualism differentiates how individuals respond to preventive measures and how investors behave on the financial market during the pandemic. This paper examines if public attention to COVID-19 in individualistic vs. collectivistic countries Granger causes Bitcoin returns between February 11, 2020 and May 09, 2022. In particular, from a time-varying perspective, it accounts for variations in the timing of COVID-19 issues across countries and circumvents the potential estimation bias that a Granger causality test could suffer, due largely to Google’s sampling variation for different time frames. By comparing eight typically individualistic and collectivistic countries, the results show that collectivistic countries present a stronger pattern of causal relationships with Bitcoin returns than individualistic countries.

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Keywords: Bitcoin; COVID-19; individualism; Google Search Volume Index; time-varying causality

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1 Introduction

Since the first known outbreak of COVID-19, Bitcoin price, at its peak, astonishingly increased by over 700%. It is demonstrated that the exploding price co-moved with the mortality of COVID-19 (Goodell and Goutte 2021), but not only deaths, confirmed cases and COVID-related news were also correlated with the Bitcoin market (Sarkodie et al. 2022; Zhang et al. 2022). The evolution, particularly, a worsening prospect, of the pandemic and the exposure to its news could effectively drive public panic. Such fears towards COVID-19 was often accompanied by a lower return close at hand, yet a reversal later on, and spurred the trading volume and volatility (Chen et al. 2020; Da et al. 2015).\footnote{Da et al. (2015) discussed return reversals.} Even for a fear not specific to COVID-19, its effects on Bitcoin returns were more persistent since the pandemic than before (Polat et al. 2022).

At the same time, the epidemic situation varies a lot between countries due, in part, to the role of cross-cultural differences in preventive behaviors and health outcomes. More individualistic regions saw less compliance with stay-at-home orders, were more reluctant to a variety of socially optimal actions, such as social distancing, mask use, or receiving vaccine, and had more cases and/or higher fatalities (Bazzi et al. 2021; Chen et al. 2021; Maaravi et al. 2021; Ozkan et al. 2021). This differential effect on compliance was found robust even at the individual level (Bian et al. 2022).

Overall, the pandemic and people’s concern over it form part of the dynamics of the Bitcoin market, while individualism and collectivism, as an element of culture, differentiate how individuals regard and react to the viral spread and corresponding measures. A question naturally comes up: do individualistic and collectivistic countries differ in influencing the Bitcoin market under the COVID-19 shock? Despite indirectly, possible answers could be drawn from the previous studies that increases in individualism was correlated with decreases in Bitcoin price co-movements (Caporale and Kang 2020); individualistic culture weakened the willingness to buy Bitcoin during the lockdown (Chen et al. 2022); national culture tends to affect how investors perceive and respond to the pandemic (Fernandez-Perez et al. 2021). However, people’s attention and the subsequent panic
and the surge of COVID-19 news and cases are subject to the time that COVID-19 and its variants occur and spread, particularly, within their countries. In other words, timing of COVID-19 issues is critical for the analysis, suggesting that causal relations between a country’s epidemic situation and the Bitcoin market could be very different time-wise, beyond a (bi-)directional causality question.2

Therefore, this paper focuses on the time-varying Granger causality between public attention to COVID-19 in individualistic vs. collectivistic countries and daily Bitcoin returns. To this end, two newly-developed time-varying Granger causality tests are adopted (Shi et al. 2020; 2018). Attention to COVID-19, retrieved from Google Trends,3 is an ideal proxy for public concern and panic.4 Further, analyzing all countries case by case is impossible in this study, so I chose the US, China, Japan, Germany, the UK, India, France, and South Korea for comparison purposes.5 In addition, GSVI data are inconsistent across time due largely to the variation in random samples drawn by Google for different time frames (Eichenauer et al. 2022),6 which could invalidate a traditional Granger causality test. With the time-varying causality tests, I control the initialization and bootstrapping procedure to be performed over a three-month window to circumvent this problem.7 Lastly, this study also relates to three other strands of literature: a growing body of literature uses time-varying Granger causality tests (e.g., Diniz et al. 2022; Hu et al. 2020); financial studies focus on the role of individualism (e.g., Salcedo and Gupta 2021; Todea and Buglea 2017); Bitcoin research exploits Google Trends data (e.g., Urquhart 2018; Zhang et al. 2021).
2 Data and Methodology

2.1 Data Source

Daily data of Bitcoin prices between February 11, 2020 and May 09, 2022 are retrieved from Bitcoincharts.\textsuperscript{8} Bitcoin return is defined as $r_t = \ln(\frac{P_t}{P_{t-1}})$. The daily attention to COVID-19 issues is measured through regional Google Search Volume Index, using “COVID” as the keyword.\textsuperscript{9} The data are briefly summarized in Table 1.

| Country | Daily GSVI Mean | Individualism Score |
|---------|-----------------|---------------------|
| **Individualism** | | |
| US | 58.68 (2nd) | 91 (highest) |
| UK | 55.45 (4th) | 89 (2 lower the US) |
| France | 49.55 (6th) | 71 (20 lower the US) |
| Germany | 65.88 (1st) | 67 (24 lower the US) |
| **Collectivism** | | |
| South Korea | 56.26 (3rd) | 18 (lowest) |
| China | 42.42 (8th) | 20 (2 higher than South Korea) |
| Japan | 50.97 (5th) | 46 (28 higher than South Korea) |
| India | 43.72 (7th) | 48 (30 higher than South Korea) |

Notes: The scale of GSVI and individualism score is 0–100 and 6–91, respectively.
Source: Google Trends & Hofstede et al. (2010).

2.2 Time-Varying Granger Causality Tests

Following Shi et al.’s (2018) procedure, an unrestricted VAR(p) model can be written as:

$$y_t = \phi_0 + \phi_1 \sum_{i=1}^{p} y_{t-i} + \epsilon_t$$

where $y_t$ is a vector of variables of interest. $\phi_0$ is a vector of constants, and $\epsilon_t$ is a vector of independent white noise innovations.

\textsuperscript{8}The World Health Organization released the official name “COVID-19” on February 11, 2020.
\textsuperscript{9}Using “COVID” obtains more inclusive results than using “COVID-19” because users don’t necessarily add “-19” to search terms. See search tips here.
The Wald test of the restrictions imposed by the null hypothesis has the general form:

\[ W = [R \text{ vce}(\hat{\Pi})]' [R(\hat{\Omega} \otimes (X'X)^{-1})R']^{-1} [R \text{ vce}(\hat{\Pi})] \]  

(2)

where vce(\hat{\Pi}) denotes the (row vectorized) 2(2p + 1) \times 1 coefficients of \hat{\Pi}, and R is the p \times 2(2p + 1) selection matrix. Each row of R picks one of the coefficients to set to zero under the non-causal null hypothesis.

Shi et al.'s (2018) propose three tests based on the supremum norm (sup) of a series of recursively evolving Wald test statistics to detect changes in causality using a forward recursive (Thoma 1994), a rolling window (Swanson 1998) and a recursive evolving algorithm (Phillips et al. 2015a; b). The origination (termination) date of a change in causality is identified as the first observation whose test statistic value exceeds (goes below) its corresponding critical value.

The Wald statistic obtained for each sub-sample regression, using observations over \([f_1, f_2]\) with a sample size fraction of \(f_w = f_2 - f_1 \geq f_0\), is denoted by \(W_{f_2}(f_1)\), and the supremum Wald statistic is defined as:

\[ \text{SW}_f(f_0) = \sup_{(f_1, f_2) \in \Lambda_0, f_2 = f} \{ W_{f_2}(f_1) \} \]  

(3)

where \(\Lambda_0 = \{(f_1, f_2) : 0 < f_0 + f_1 \leq f_2 \leq 1, and 0 \leq f_1 \leq 1 - f_0\}\) for some minimal sample size \(f_0 \in (0, 1)\) in the regressions. This is the so-called recursive evolving procedure.

Let \(f_e\) and \(f_f\) denote the origination and termination points in the causal relationship that are estimated as the first chronological observation whose test statistic exceeds or falls below the critical value. Because the power of the recursive evolving procedure is found to be best, and both the recursive evolving and rolling procedure perform much better than the forward recursive procedure (Shi et al. 2020; 2018), the analysis relies on dating rules of the following two algorithms:

\[ \text{Rolling} : \hat{f}_e = \inf_{f \in [f_0, 1]} \{ f : W_f(f - f_0) > \text{cv} \} \text{ and } \hat{f}_f = \inf_{f \in [\hat{f}_e, 1]} \{ f : W_f(f - f_0) < \text{cv} \} \]

\[ \text{Recursive Evolving} : \hat{f}_e = \inf_{f \in [f_0, 1]} \{ f : \text{SW}_f(f_0) > \text{scv} \} \text{ and } \hat{f}_f = \inf_{f \in [\hat{f}_e, 1]} \{ f : \text{SW}_f(f_0) < \text{scv} \} \]  

(4)
where $cv$ and $scv$ are the corresponding critical values of the $W_f$ and $SW_f$ statistics. For multiple switches, the origination and termination dates are estimated in a similar fashion. All procedures are implemented under the null hypothesis of no causality and under the assumption of either homoskedasticity or conditional heteroskedasticity of an unknown form.

3 Empirical Results

To estimate the VAR model and implement the aforementioned tests, the Bayesian information criteria (BIC) with a maximum potential lag length 12 are used for selecting the lag order. The minimum window size $f_0$ is set to be three months. Critical values are obtained from a bootstrapping procedure with 499 replications. The empirical size is 5% and controlled over a three-month period. Further, the Augmented Dickey-Fuller (ADF) and Phillips-Perron unit root tests suggest that Bitcoin returns and daily attention are all stationary (p-value $< 1\%$ for all).

3.1 Individualistic Countries

The results of the recursive evolving tests running from the public attention to COVID-19 in the US, Germany, the UK, and France to Bitcoin returns are displayed in Figures 1–4. As seen in Figure 1, two Wald tests detect that no statistic sequence exceeds its corresponding critical values, indicating that the null hypothesis of no Granger causality cannot be rejected for the US. While, in Figure 2, a very short causal episode around November 01, 2021 is identified for the UK. Further, the results between two Wald tests (homoskedastic vs. heteroskedastic) with regard to Germany are quite dissimilar – although no causality can be learned in Figure 3(a), when taking into account the potential heteroskedasticity in the data, two causal episodes are found, as shown in Figure 3(b). In particular, the time span of the second causal episode is much longer than the first, lasting for approximately 108 days. Likewise, attention paid by people living in France to the pandemic had

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10Non-stationary variables can also be tested with the same algorithms using the lag-augmented VAR approach, as shown in Shi et al. (2020).
11Test results using rolling window algorithms are reported in the Appendix.
an impact on Bitcoin returns during at least two periods, among which the latest one was arose on January 22, 2022 and terminated on February 14, 2022. In general, no sufficient evidence can be drawn that people’s concern over epidemic situations in these individualistic countries has an impact on Bitcoin returns.

Figure 1: Tests for Granger causality running from public attention to COVID-19 in the US to Bitcoin returns. Notes: The test statistic sequence (——) is in black; the 5% bootstrapped critical value sequence (―) is in red. The selected lag order is 1.

Figure 2: Tests for Granger causality running from public attention to COVID-19 in the UK to Bitcoin returns. Notes: The test statistic sequence (——) is in black; the 5% bootstrapped critical value sequence (―) is in red. The selected lag order is 1.
Figure 3: Tests for Granger causality running from public attention to COVID-19 in Germany to Bitcoin returns. Notes: The test statistic sequence (—) is in black; the 5% bootstrapped critical value sequence (–) is in red. The selected lag order is 1.

Figure 4: Tests for Granger causality running from public attention to COVID-19 in France to Bitcoin returns. Notes: The test statistic sequence (—) is in black; the 5% bootstrapped critical value sequence (–) is in red. The selected lag order is 1.
3.2 Collectivistic Countries

The results of the recursive evolving tests running from the attention to COVID-19 in India, China, Japan, and South Korea to Bitcoin returns are presented in Figures 5–8. Here, all the countries with two Wald tests show at least one causal episode. As seen in Figure 5, the public attention to COVID-19 in India exhibits two short episodes of causality around November 24, 2020 and January 12, 2022. Similarly, three episodes are found for China, while the longest one started on January 19, 2021 and lasted for approximately 33 days with a bit of interruptions. In contrast, people’s attention to COVID-19 in Japan and South Korea is found to have much stronger causal links with Bitcoin returns in both length and magnitude. In particular, the results with regard to Japan are remarkable – the causality existed for almost the whole sample period. While the longest causal episode related to South Korea is also more persistent than other countries, except for Japan. To be specific, it occurred around June 21, 2021 and lasted for approximately 196 days. Overall, collectivistic countries here show a stronger pattern of causal relationships with Bitcoin returns than individualistic countries.

Figure 5: Tests for Granger causality running from public attention to COVID-19 in India to Bitcoin returns. Notes: The test statistic sequence (—) is in black; the 5% bootstrapped critical value sequence (−) is in red. The selected lag order is 1.

Test results using rolling window algorithms are reported in the Appendix.

The interpretations rely mainly on the results of the heteroskedastic-consistent test.
Figure 6: Tests for Granger causality running from public attention to COVID-19 in China to Bitcoin returns. Notes: The test statistic sequence (—) is in black; the 5% bootstrapped critical value sequence (–) is in red. The selected lag order is 1.

Figure 7: Tests for Granger causality running from public attention to COVID-19 in the Japan to Bitcoin returns. Notes: The test statistic sequence (—) is in black; the 5% bootstrapped critical value sequence (–) is in red. The selected lag order is 9.
4 Conclusions

This paper adopted two novel time-varying Granger causality tests to examine the relationships between public attention to COVID-19 in individualistic vs. collectivistic countries and Bitcoin returns. Eight typically individualistic and collectivistic countries that are economically powerful were chosen for analyses. It is found that collectivistic countries here present a stronger pattern of causal relationships with Bitcoin returns than individualistic countries. The results are consistent with the previous studies (e.g., Caporale and Kang 2020; Chen et al. 2022) and add a new angle and insights to the Bitcoin literature on individualism and COVID-19.

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Appendix: Figures
Figure 9: Tests for Granger causality running from public attention to COVID-19 in the US to Bitcoin returns. Notes: The test statistic sequence (—) is in black; the 5% bootstrapped critical value sequence (–) is in red. The selected lag order is 1.

Figure 10: Tests for Granger causality running from public attention to COVID-19 in Germany to Bitcoin returns. Notes: The test statistic sequence (—) is in black; the 5% bootstrapped critical value sequence (–) is in red. The selected lag order is 1.
Figure 11: Tests for Granger causality running from public attention to COVID-19 in the UK to Bitcoin returns. Notes: The test statistic sequence (—) is in black; the 5% bootstrapped critical value sequence (–) is in red. The selected lag order is 1.

Figure 12: Tests for Granger causality running from public attention to COVID-19 in France to Bitcoin returns. Notes: The test statistic sequence (—) is in black; the 5% bootstrapped critical value sequence (–) is in red. The selected lag order is 1.
Figure 13: Tests for Granger causality running from public attention to COVID-19 in India to Bitcoin returns. Notes: The test statistic sequence (—) is in black; the 5% bootstrapped critical value sequence (–) is in red. The selected lag order is 1.

Figure 14: Tests for Granger causality running from public attention to COVID-19 in China to Bitcoin returns. Notes: The test statistic sequence (—) is in black; the 5% bootstrapped critical value sequence (–) is in red. The selected lag order is 1.
Figure 15: Tests for Granger causality running from public attention to COVID-19 in the Japan to Bitcoin returns. Notes: The test statistic sequence (—) is in black; the 5% bootstrapped critical value sequence (–) is in red. The selected lag order is 9.

Figure 16: Tests for Granger causality running from public attention to COVID-19 in South Korea to Bitcoin returns. Notes: The test statistic sequence (—) is in black; the 5% bootstrapped critical value sequence (–) is in red. The selected lag order is 2.
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