Time-varying dependence between Bitcoin and green financial assets: a comparison between pre- and post-COVID-19 periods

Article

Accepted Version

Huang, Yingying, Duan, Kun and Urquhart, Andrew ORCID logoORCID: https://orcid.org/0000-0001-8834-4243 (2023) Time-varying dependence between Bitcoin and green financial assets: a comparison between pre- and post-COVID-19 periods. Journal of International Financial Markets, Institutions and Money, 82. 101687. ISSN 1042-4431 doi: https://doi.org/10.1016/j.intfin.2022.101687 Available at https://centaur.reading.ac.uk/108708/

To link to this article DOI: http://dx.doi.org/10.1016/j.intfin.2022.101687

Publisher: Elsevier

Time-varying Dependence between Bitcoin and Green Financial Assets: A Comparison between Pre- and Post-COVID-19 Periods

Yingying Huang[a], Kun Duan[b,*], Andrew Urquhart[c]

[a]*School of Management, Harbin Institute of Technology, 150000, China.*
[b]*School of Economics, Huazhong University of Science and Technology, 430074, China.*
[c]*ICMA Centre, Henley Business School, University of Reading, RG6 6BA, UK.*

Abstract

This paper studies the time-varying market linkages between Bitcoin and green assets before and during the COVID-19 pandemic through a TVP-VAR model with stochastic volatility. Both the roles of uncertainty and environmental attention related to cryptocurrency are considered when modeling market linkages, which underlying asymmetry is detected from three perspectives, i.e., bidirectionality of the impact direction, time points where the unit shock of the IRF analysis is imposed, and before and after the pandemic. We find that the investment sheltering role of Bitcoin for green assets is enhanced and expanded after the onset of the pandemic, while green assets in turn consistently act as an effective hedge for Bitcoin irrespective of the pandemic. Additional analyses confirm the robustness of our findings, which possess implications for not only hedging against green portfolios but also seeking green shelters.

Keywords: Bitcoin; Green financial assets; Time-varying dependence; Asymmetry; COVID-19

*Corresponding author.

Email addresses: huangyingying@hit.edu.cn (Yingying Huang), kduan15@outlook.com (Kun Duan), a.j.urquhart@icmacentre.ac.uk (Andrew Urquhart)

1. Introduction

Over the past number of decades, climate change has become one of the most serious issues facing the world, calling for a global agenda for green and sustainable development in the future. However, over the last decade, cryptocurrencies have been developed and become more and more popular which are known to have high energy consumption with adverse environmental impacts[1] while attention on the future green development of the cryptocurrency market remains surprisingly scant (Corbet et al., 2021). As one of the leading cryptocurrencies, Bitcoin has soared in value in recent times but still faces concerns from academics and investors alike on whether to include this 'dirty currency' into the investment portfolio or not (Naeem and Karim, 2021). The recent headline pulled by the strategic withdrawal of Tesla's acceptance of cryptocurrencies purchase due to environmental concerns has further drawn widespread attention of the power consumption and carbon emission issues of Bitcoin transactions. Accordingly, there exists an ongoing debate in academia and financial markets on whether to incorporate green assets into Bitcoin-related portfolios for dual goals of risk diversification and green investment commitment.

In parallel, the unprecedented COVID-19 pandemic has not only incurred vast changes to the everyday life to individuals but have had profound effects on operations of economic and financial systems (Huang et al., 2021). Since literature suggests that financial assets have become more correlated in the bust periods (Hartmann et al., 2004; Lee et al., 2011), acute economic losses incurred by the ongoing Covid019 pandemic therefore provides a critical test-bed for the dynamics of financial market co-movement and the potential investment shelters in the downturn (Goodell, 2020). Recently, Bitcoin, being recognized as 'liquid gold' due to its independence from political and economic tones of sovereign nations, has raised widespread discussion on its potential sheltering role during a market crash (Yarovaya et al., 2020). At the same time, it is pointed out that market dependence between Bitcoin

[1] For instance, see https://www.forbes.com/advisor/investing/bitcoins-energy-usage-explained/.

and financial assets features a time-varying pattern, indicating that the degree of hedging and safe-haven properties of Bitcoin, if any, tends to evolve over time instead of being constant (Shahzad et al., 2019; Ren et al., 2022). Thus, the above entails careful reexamination of the role of the pandemic in time-varying spillovers of financial markets, particularly the dynamic dependence between Bitcoin and green assets in our case.

Against this background, this paper examines the time-varying market dependence between Bitcoin and green financial assets before and during the COVID-19 pandemic through a time-varying parameter VAR (TVP-VAR) model with stochastic volatility. To study the role of the pandemic on the market dependence, we have followed extant literature (see, e.g., Goodell and Goutte, 2021b; Huang et al., 2021) by considering two sub-samples before and after the pandemic onset with the whole daily dataset spanning from September 2018 to September 2021. The dynamics and asymmetry of the market dependence are studied from three perspectives, i.e., various time horizons, before and during the pandemic, and bidirectional market relations, respectively. The time-varying impulse response function (IRF) analysis identified by our TVP-VAR model with stochastic volatility is conducted to study the potentially dynamic market dependence over time. In addition, green financial assets are represented by individual indices including the Dow Jones Sustainability World Index (SWI), S&P ESG Leader Index (ESGLI), S&P Green Bond Index (GBI), and S&P Global Clean Energy Index (GCEI).

Moreover, the uncertainty in social and economic conditions could alter investors' anticipation, and the weakening of which further triggers the financial turmoil, leading to fluctuations in the cryptocurrency market (Wu et al., 2022). At the same time, it is also known that uncertainty from different perspectives could exert varying impacts and predictive power on the cryptocurrency market (Lucey et al., 2021b). While rising uncertainty plays a key role in the cryptocurrency market dynamics, the commonly-used index such as economic policy uncertainty involves various sectors in the economy, which may not offer a sufficiently-accurate measure for the uncertainty in the field of cryptocurrency. There has long been a devoid of an uncertainty indicator that is specifically designed for the cryptocurrency until the recently-developed cryptocurrency uncertainty indices by Lucey et al. (2021b). We therefore employ the two indices by Lucey et al. (2021b) that capture the sizes of unpredictable disturbances in price and policy of cryptocurrencies, respectively. The two indices are Uncertainty of Cryptocurrency Policy (UCRY Policy) and Uncertainty of Cryptocurrency Price (UCRY Price). Moreover, growing energy consumption caused by cryptocurrency mining and its related emission issues have raised emerging environmental concerns about the cryptocurrency. We therefore further incorporate the Cryptocurrency Environmental Attention Index (ICEA) proposed by Lucey et al. (2021a) that measures the extent of environmental sustainability concerns on the cryptocurrency trading by the public. This enables us to determine how the linkages vary under different attention levels for cryptocurrency environmental issues. Therefore, in our paper, the cross-market linkage between Bitcoin and green assets will be investigated in a setting where the uncertainty and environmental attention for the cryptocurrency are well considered.

Our paper is closely linked to the extant literature in the following three strands, market dependence of Bitcoin with financial assets and commodities, investment sheltering role of Bitcoin, and the role of COVID-19 pandemic in the market interaction, with a particular focus on the time-varying market linkage between Bitcoin and green financial assets. Specifically, existing studies has examined the market interaction between Bitcoin and general financial markets of assets and commodities with some further discussion on the sheltering role of Bitcoin for financial assets and the other way round (e.g., Bouri et al., 2018; Urquhart and Zhang, 2019; Conlon et al., 2020; Corbet et al., 2021; Wang et al., 2021; Duan et al., 2021a,b). Amongst others, Conlon et al. (2020) and Goodell and Goutte (2021b) examine the potential role of cryptocurrencies as a safe-haven or diversifier on equity indices during the COVID-19 period. Maghyereh and Abdoh (2020) employ a quantile cross-spectral approach to examine the tail dependence between prices of Bitcoin and financial indicators including S&P 500 and exchange rate. Regarding the linkage between cryptocurrencies and commodity markets, including gold and various commodities such as energy, metals, and agricultural products, Le et al. (2021a) measure the spillover pattern between prices of Bitcoin and other assets including stock and gold, and find the consistent safe-haven property of gold in the post-COVID-19 period. Rehman and Kang (2021) point out a lead-lag connection between Bitcoin and crude oil market.

Moreover, although being limited and ongoing, the market dependence between cryptocurrencies notably including Bitcoin and green financial indices have been investigated with studies determining whether the linkage is uni- or bi-directional, and whether it varies over time remains unclear (e.g., Okorie, 2021; Symitsi and Chalvatzis, 2018). For instance, Symitsi and Chalvatzis (2018) show that there exists unidirectional return and volatility interactions between Bitcoin and green financial assets represented by stock indices of energy and technology firms, while shock interactions are found to be bi-directional. As for the potential investment shelter role for green financial assets against adverse market fluctuations of cryptocurrencies, consensus has yet to be reached in existing empirical analyses (e.g., Naeem and Karim, 2021; Lucey et al., 2021a). For example, Naeem and Karim (2021) point out that green financial assets such as clean energy indices act as hedges for Bitcoin. Ren and Lucey (2021) show that stock prices of clean energy would not be a direct hedge but safe-haven for both 'dirty' and 'clean' cryptocurrencies. Thus, the above demonstrates that consensus of existing findings on the market interdependence between cryptocurrencies and green energy indices has not yet been reached.

In addition, growing attention focuses on the role of COVID-19 pandemic in the financial market linkage. Given that the later could become more connected during the economic downturn (Hartmann et al., 2004), the market depression associated with onset of the ongoing pandemic offers a critical testbed in this regard (Huang et al., 2021). Recent literature studies the impact of the pandemic on the co-movement between markets of financial assets including Bitcoin and commodities under uncertainty (Aloui et al., 2020; Sharif et al., 2020), as well as the sheltering role of Bitcoin against financial assets and commodities (Conlon et al., 2020; Conlon and McGee, 2020). While it has been pointed out that the market dynamics of financial assets including cryptocurrencies could be altered by the pandemic (Goodell and Goutte, 2021a), research on the pandemic impact on the market nexus between Bitcoin and green financial remains surprisingly scant by far.

Our paper contributes to the extant related literature in the following aspects. First, rather than a conventional VAR model that only reports fixed coefficient estimates, we employ a TVP-VAR model with stochastic volatility. Through this, the potential time-varying property of variable relationships in both matrices of coefficient and covariance is respectively identified. Moreover, our employed method offers a time-varying IRF analysis that outperforms the conventional IRF by capturing the variable response in the face of a unit structural shock being imposed at different time points, such as the first quarter, the half year, and the third quarter, respectively, in our case. Overall, to the best of our knowledge, our paper is among the first that investigates the possibly asymmetric and time-varying market information spillovers between Bitcoin and green financial assets, while considering related financial indicators notably including the cryptocurrency uncertainty index and the index of cryptocurrency environmental attention.

We find that the market dependence between Bitcoin and the four considered green financial assets is asymmetric from three perspectives, namely impact directions, time points where the unit shock is being imposed in the IRF analysis, as well as before and during the COVID-19 pandemic. As for the contemporaneous market relationship, Bitcoin is found to act as an investment shelter of effective hedge for the specific green asset GCEI before the pandemic, while its effective hedging role is further enhanced and extended to three green financial assets, i.e., SWI, ESGLI, and GCEI, after the pandemic onset at different time horizons. Conversely, the four green financial assets play an effective hedge for Bitcoin, and such the role remains constant irrespective of the pandemic. The mutually reinforcing and enhanced investment sheltering ability between Bitcoin and green assets over time corroborates with the extant literature, and is supported by no or even a negative relationship between the two agents. The underlying reason has been discussed from two perspectives, i.e., green economic transition and dynamics of production costs in terms of rising energy prices. In addition, several additional analyses are conducted to demonstrate that our findings are robust to various changes in the research design. Our research is of important implications as to whether there exists a green investment shelter against adverse fluctuations of Bitcoin, and the sheltering role of Bitcoin for green portfolios.

The rest of this paper is structured as follows. Section 2 discusses our empirical data with preliminary analysis. Section 3 introduces our employed methodology. Section 4 analyzes empirical results. Section 5 discusses the analysis of robustness checks. The last section concludes with a discussion on policy implications.

2. Data and Preliminary Analysis

Our research dataset includes Bitcoin price (BTC), four green financial assets (i.e., SWI, ESGLI, GBI, and GCEI), three indices describing the cryptocurrency market condition through both perspectives of uncertainty (i.e., URCY policy and URCY price) and environmental sustainability (ICEA), and the CBOE Volatility Index (VIX). In spirit of the extant literature (e.g., Goodell and Goutte, 2021b; Huang et al., 2021), the research period spans from 01 September 2018 to 30 September 2021, and is divided into two sub-samples on 11 March 2020, which is the first day when the COVID-19 was announced as a pandemic by the WHO[2]. Accordingly, sub-samples of 01 September 2018 - 10 March 2020 and 11 March 2020 - 30 September 2021 are used to represent pre- and post-COVID-19 periods, respectively.

Regarding the Bitcoin price series, it is represented by the Coindesk Price Index from www.coindesk.com, which represents an average of Bitcoin prices across leading Bitcoin exchanges worldwide.[3] The four green financial assets involve Dow Jones Sustainability

[2]See details about key dates of COVID-19 announced by the WHO at https://www.who.int/emergencies/diseases/novel-coronavirus-2019/interactive-timeline.

[3]The Coindesk Price Index is the data source commonly used in the literature (e.g. Kwon, 2020; Baur

World Index (SWI), S&P ESG Leader Index (ESGLI), S&P Green Bond Index (GBI), and S&P Global Clean Energy Index (GCEI), and are from S&P Dow Jones Indices database (www.spglobal.com/spdji). The three cryptocurrency market related indices contain Uncertainty of Cryptocurrency Policy Index (UCRY Policy), Uncertainty of Cryptocurrency Price Index (UCRY Price), and Cryptocurrency Environmental Attention Index (ICEA). They are sourced from Lucey et al. (2021a,b) that extracts news from the LexisNexis News & Business database[4]. The VIX series is archived from COBE database (www.cboe.com).

[Figure 1 about here.]

Temporal dynamics of the price series of Bitcoin, green financial assets, indices of cryptocurrency market condition, and VIX are drawn in Figure 1, respectively. Particularly, it can be seen that all considered series except the VIX have witnessed a dramatic drop on 11 March 2020, i.e., the announcement date of COVID-19 as a pandemic. At the same time, the VIX index peaked on the announcement date and then plunged, showing marked volatility of financial markets induced by the pandemic. This also provides a visual demonstration regarding the separation of our whole data to investigate the pandemic impact on the cross-market linkages. For each of the considered series, it is transformed in the return format as the first-order log difference between the current day and the last day times 100 of the original series, i.e., $R_t = (\log(P_t) - \log(P_{t-1}))$. Table 1 shows the descriptive statistics for each transformed series in subsamples of pre- and post-COVID-19 periods, respectively. Briefly, the return-transformed Bitcoin price index, green financial assets, and indices of cryptocurrency market condition are found to possess larger mean values with higher standard deviations since the COVID-19 is announced as a pandemic. At the same time the mean value of return-transform VIX index turned to be negative with relatively lower volatility in the post-COVID-19 period compared to that in the pre-COVID-19 period, being consistent

et al., 2018; Bouri et al., 2019; Kapar and Olmo, 2019)

[4] See details about data of UCRY Policy, UCRY Price, ICEA at https://lnkd.in/egtcZvzS.

with the existing findings (e.g., Lucey et al., 2021a,b; Naeem and Karim, 2021).

[Table 1 about here.]

3. Methodology

3.1. Time-Varying Parameter VAR with Stochastic Volatility

The time-varying parameter VAR (TVP-VAR) model with stochastic volatility is known to outperform the conventional VAR method and has been widely applied to modelling the dynamic relationship between macroeconomic and financial indicators (e.g., Chan and Eisenstat, 2018; Clark and Ravazzolo, 2015; D'Agostino et al., 2013; Nakajima et al., 2011). It not only considers the potential time-varying feature of the underlying structure, but also accommodates the fluctuating disturbance, particularly in the financial turmoil. Therefore, we employ the TVP-VAR model with stochastic volatility for clearer comprehension on the relationship between price returns of Bitcoin and green financial assets by considering the condition of the cryptocurrency market through aspects of uncertainty, environmental sustainability, and financial volatility.

The model departs from a k-dimensional return vector R_t that involves Bitcoin prices BTN_t, four green financial asset prices $GFA_t' = (SWI_t, ESGLI_t, GBI_t, GCEI_t)'$, three cryptocurrency market related indices $CRI_t' = (UCRYPolicy_t, UCRYPrice_t, ICEA_t)'$, and the financial market volatility VIX_t at period t $(t = 1, \ldots, T)$. The TVP-VAR model with stochastic volatility is then formulated as: framework is formulated as

$$R_t = B_{1t}R_{t-1} + \ldots + B_{pt}R_{t-p} + \varepsilon_t, \quad \varepsilon_t \sim N\left(0, A_t^{-1}\Sigma_t\epsilon_t\right), \tag{1}$$

for $t = p+1, \ldots, n$, where $B_{1t}, \ldots, B_{pt}$ are $k \times k$ autoregressive coefficient matrices with the number of variables k and lags of p. ϵ_t refers to a $k \times 1$ structural shocks with A_t being identified as a lower triangular covariance matrix, Σ_t being as a diagonal matrix of stochastic volatility, and $\epsilon_t \sim N(0, I)$. The structures of A_t and $Sigma_t$ are presented as follows:

$$A_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1,t} & \cdots & a_{k,(k-1),t} & 1 \end{bmatrix} \quad \text{and} \quad \Sigma_{\mathrm{t}} = \begin{bmatrix} \sigma^2_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma^2_{2,t} & \ddots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & \sigma^2_{k,t} \end{bmatrix}.$$

Let $X_t = \left(R'_{t-1}, \ldots, R'_{t-p}\right)'$ and $B'_t = (B_{1t}, \ldots, B_{pt})$, the model can be rewritten in a more compact form:

$$R_t = B'_t X_t + \varepsilon_t. \tag{2}$$

To better model the potentially time-varying relationship between macro-financial variables in the TVP-VAR model, the coefficients of B_t, covariance matrix of A_t, and stochastic volatility of Σ_t are allowed to vary over time. To model the time-varying coefficients, we define $\beta_t = \mathrm{vec(B_t)}$, by assuming that β_t follows a random walk process with $t = p+1, \ldots, n$,

$$\beta_t = \beta_{t-1} + u_t, \quad u_t \sim N\left(0, \Sigma_\beta\right). \tag{3}$$

Similarly, we construct a_t as a row-wise stacked vector of the lower-triangular covariance elements of A_t, i.e., $a_t = (a_{21,t}, \ldots, a_{k,k-1,t})'$ and σ^2_t as a vector of the diagonal elements of Σ_t, i.e., $\sigma^2_t = \left(\sigma^2_{1,t}, \ldots, \sigma^2_{k,t}\right)'$, following Primiceri (2005). Both a_t and σ^2_t are assumed to follow a random walk process, and we have

$$a_t = a_{t-1} + \vartheta_t, \qquad \vartheta_t \sim N\left(0, \Sigma_a\right), \tag{4}$$

$$\log(\sigma_t) = \log(\sigma_{t-1}) + v_t, \qquad v_t \sim N\left(0, \Sigma_\sigma\right), \tag{5}$$

Therefore, the vector involving the innovations to the structural shocks ε_t (ϵ_t), time-varying coefficients β_t (u_t), and stochastic volatilities of a_t (ϑ_t) and $\log(\sigma^2_t)$ (v_t) is known to follow the below distribution

$$\begin{bmatrix} \epsilon_t \\ u_t \\ \vartheta_t \\ v_t \end{bmatrix} = \begin{bmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_\sigma \end{bmatrix}. \tag{6}$$

Given that our TVP-VAR model with stochastic volatility is featured by large time-varying parameters as specified in Equations (3) to (5), we will discuss in Section 3.3 regarding how the Bayesian approach using a Markov chain Monte Carlo (MCMC) algorithm is employed to estimate the model.

3.2. Shock Identification

To identify the structural shock in our TVP-VAR model with stochastic volatility, we conduct a Cholesky decomposition for the covariance matrix of Σ_t, as shown in Section 3.2. We order the target series following the existing literature (e.g., Lucey et al., 2021a,b; Naeem and Karim, 2021) as:

$$R_t = (UCRY\,Policy_t, VIX_t, BTN_t, SWI_t, ESGLI_t, GBI_t, GCEI_t, UCRY\,Price_t, ICEA_t)\,. \tag{7}$$

Regarding the reason for the above ordering, in line with Lucey et al. (2021a,b), the series of the cryptocurrency policy uncertainty (UCRY policy) index is ordered first since that series such as VIX and Bitcoin can react instantaneously to uncertainty policy shocks. Given that other considered series are known to react faster than UCRY price index, the latter is accordingly ordered behind with the index of environmental sustainability of the cryptocurrency market (ICEA) being ordered last. Moreover, it is further worth noting that ordering Bitcoin before green financial assets is consistent with Naeem and Karim (2021).

3.3. Estimation Algorithm

The Bayesian method is applied to estimate our TVP-VAR model with stochastic volatility, wherein the MCMC algorithm is conducted using a simulation-based estimation that generates a sequence of draws from the full conditional distributions of all parameters. The time-varying parameters can be well estimated through a nested structure that computes the likelihood function for each iteration process. To enforce the MCMC algorithm, the following conditional distributions are formulated:

$$\begin{aligned} &\beta_t \big| a_t, \sigma_t^2, \Sigma_\beta, \\ &a_t \big| \beta_t, \sigma_t^2, \Sigma_a, \\ &\sigma_t^2 \big| \beta_t, a_t, \Sigma_\sigma, \\ &\Sigma_\beta \big| \beta_t, \\ &\Sigma_a \big| a_t, \\ &\Sigma_\sigma \big| \sigma_t^2. \end{aligned} \tag{8}$$

Detailed discussions of drawing samples from the above conditional posterior distributions with priors follow the MCMC procedures of Chen et al. (2020) and Nakajima et al. (2011), where σ_t^2 is illustrated as $\exp(h_t)$.

4. Empirical Results

4.1. Parameter Estimates

To examine the spillover pattern between price returns of Bitcoin and green financial assets while considering related financial indicators (i.e., cryptocurrency market related indices and VIX), and investigate its potential dynamics over time before and during the COVID-19 pandemic, we conduct the estimation by using the time-varying VAR (TVP-VAR) model with stochastic volatility in the two subsamples, respectively. The lag order of the TVP-VAR system is set to be 1,[5] and jointly given that there are nine variables in total included in the system, the estimated parameters therefore include 81 autoregressive coefficients (β_t), 36 covariance parameters (a_t), and 9 volatility parameters (σ_t^2) for the pre- and post-COVID-19 periods, respectively. Overall, with a particular focus on the time-varying relationships of Bitcoin with green assets and related financial indicators, Figures 2 and 3 show dynamics of the posterior draws of β_t over time before and during the COVID-19 pandemic; panels (a) and (b) of 4 and 5 present dynamic plots of the posterior draws of a_t and σ_t^2 over time before and after the announcement of the pandemic, respectively. The above time-varying dynamics are depicted in the x-axis of the corresponding figures where the period of 01 September 2018 - 11 March 2020 denotes the period before the pandemic and 12 March 2020 - 30 September 2021 denotes the one during the pandemic.

[Figure 2 about here.]

[Figure 3 about here.]

With regard to the time-varying posterior estimates of β_t, the role of Bitcoin in driving other series and the other way around exhibit distinct results over time, as shown in Figures 2 and 3. We find the potentially bi-directional relationships of Bitcoin prices with green financial asset prices (i.e., SWI, ESGLI, GBI, and GCEI) and related financial indicators including indices for the cryptocurrency market condition through perspectives of uncertainty (URCY Policy and URCY Price) and environmental sustainability (ICEA), and VIX generally remain stable and unchanged overtime before and after the outbreak of the COVID-19. Interestingly, it is worth noting that time-varying coefficients that show the relationship between Bitcoin prices and related financial indicators are found to be less significant at most of the time.

[5]While there is no theoretical guidance for the lag order selection in the time-varying parameter (TVP) VAR system, in the empirical analysis, we have tried different order numbers, e.g., 2, 3, 4, or 5. The results are consistent with that of our benchmark estimation, and they are available from the authors upon request.

[Figure 4 about here.]

Moreover, the time-varying posterior estimates of a_t, and σ_t^2 experience a relatively marked fluctuation before and after announcement of the COVID-19 pandemic. As shown in Figures 3, it is clear that the systematic relationship (i.e., covariance shown by a_t) of Bitcoin prices with price indices of green financial assets and related financial indicators could be time-varying and sensitive to the COVID-19 pandemic, such as the relationship of Bitcoin with SWI and UCRY price; at the same time, the estimates of a_t for the correlations of Bitcoin with URCY Policy and VIX tend to be time-invariant. In addition, the dynamic time-varying pattern of the covariance of Bitcoin prices with prices of green financial assets is found to be different and even reserved in pre- and post-COVID-19 periods, while the counterpart of that with financial related indicators is shown to be relatively constant in the two sub-samples.

[Figure 5 about here.]

As for the estimates of σ_t^2 displayed in Figure 5, estimated variances of price indices of green financial assets and related financial indicators are shown to be time-varying with different patterns before and after the announcement of the pandemic. It is worth mentioning that σ_t^2 of most of the green financial assets increases (except for that on ESGLI), while that on indices related to the cryptocurrency market condition tend to decrease as time evolving to the post-COVID-19 period.

4.2. Time-varying impacts of Bitcoin on green financial assets and related financial indicators

Whether and how the impact of Bitcoin prices on green financial asset prices and related financial indicators (i.e., indices of the cryptocurrency market condition from perspectives of uncertainty and environmental sustainability and the VIX index) varies over time before and after the announcement of the COVID-19 as a pandemic? To answer this question, we conduct the time-varying impulse response function (IRF) analysis based on the parameter estimates of the employed TVP-VAR model with stochastic volatility. Rather than the conventional IRF that only observes variable response after receiving a unit shock to a target variable at the initial time point (i.e., time 0), the IRF produced by the TVP-VAR model with stochastic volatility captures potential variations of the variable response after receiving a unit shock at different time points. That is, the variable response is allowed to be time-varying once receiving a shock to a target variable at different time points, viz., the first quarter, the half year, and the third quarter, respectively, in our case. Since its initial development by Cogley and Sargent (2001, 2005) and Primiceri (2005), it has been raised an increasing attention by related literature (e.g., Chan and Eisenstat, 2018; Clark and Ravazzolo, 2015; D'Agostino et al., 2013). Time variations of responses of green financial asset prices and related financial indicators are plotted as shown in Figures 6 and 7 once receiving a unit shock to Bitcoin prices in the first quarter, the half year, and the third quarter, respectively. The potential different pattern of the time-variations in the pre- and post-periods of the COVID-19 pandemic is compared and shown in Panels (a) and (b) of the two figures, respectively. Overall, the variable responses are shown to have relatively consistent tendency while having different magnitudes once receiving the Bitcoin price shock on the three different time points. The variable responses during the COVID-19 period demonstrate a different dynamic pattern compared to that before the COVID-19 period.

[Figure 6 about here.]

Specifically, once receiving a unit shock to Bitcoin prices before the COVID-19 pandemic, as shown in Panel (a) of Figure 6, the contemporaneous responses of three of the four selected green financial asset prices, i.e., prices of SWI, ESGLI, and GBI, are shown to be positive, quickly turn to become negative after a short period, and eventually revert to zero after around four horizons. At the same time, the response pattern of the specific green financial asset (GCEI) price is shown to be reversed that it receives a negative and instant move, and quickly reverts to zero within around four horizons. The above response pattern is found to be consistent regardless of when the unit shock to Bitcoin prices is received, while the response magnitude varies over horizons with different time points for the shock impulse. Once receiving a unit shock to Bitcoin prices after the COVID-19 pandemic, as shown in Panel (b) of Figure 6, the time-varying responses of both GBI and GCEI are shown to have a broadly similar pattern as their counterparts shown before the COVID-19 pandemic; in contrast, the responses of SWI and ESGLI reverse after the pandemic announcement. In addition, the sizes of responses of each of the four green financial asset prices are found to be relatively similar once the shock to Bitcoin prices is at different time points.

[Figure 7 about here.]

Regarding the time-varying responses of related financial indicators to a unit shock of Bitcoin prices, both response path and magnitude are shown to be distinct before and after the announcement of the COVID-19 pandemic. In Panel (a) of Figure 7, it can be seen that cryptocurrency market related indices for policy and price uncertainty, i.e., URCY policy and URCY price, depict a negative instant response although with different degrees and then revert to zero after four horizons in the pre-COVID-19 period. At the same time, the cryptocurrency market related index for environmental sustainability (ICEA) and the VIX index broadly exhibit a positive response and then go back to zero with different response sizes; this pattern for ICEA particularly applies only to short time points. In contrast, after announcement of the COVID-19 pandemic, as shown in Panel (b) of Figure 7, time-varying patterns of the responses of the four related financial indicators differ compared with that before the pandemic. For example, the response of the VIX index totally turns become negative against a positive response before the pandemic. Importantly, it is worth mentioning that responses of each of the green financial asset prices and related financial indicators are shown to be time-varying instead of being constant, depending on the time points when a unit shock is imposed on the Bitcoin price, i.e., the first quarter, the half year, and the third quarter, respectively, in our case.

Importantly, regarding the contemporaneous relationship, before the COVID-19 pandemic, Bitcoin prices exert positive impacts on prices of three out of the four target green financial assets, i.e., SWI, ESGLI, and GBI, except for the price of GCEI , which is influenced negatively, at various time horizons. Such positive impacts on prices of SWI and ESGLI turn to become negative during the pandemic, while the respective positive and negative impacts on GBI and GCEI are shown to be consistent in the face of the pandemic outbreak. It can be therefore found that Bitcoin acts as an investment shelter on the specific green financial asset GCEI before the pandemic, while its sheltering role is enhanced and further expanded to three green financial assets, i.e., SWI, ESGLI, and GCEI, during the pandemic. As for indices related to the cryptocurrency market condition, Bitcoin is found to perform a consistent zero contemporaneous impact on URCY policy and VIX in both subsamples before and after the pandemic onset, while its sheltering role for UCRY price is only effective before the pandemic. Our results of the investment sheltering property of Bitcoin against various financial indicators corroborate with existing literature (Huang et al., 2021; Le et al., 2021a). The hedging role of Bitcoin against green assets is found to be further enhanced after the pandemic onset over time as supported by the weakened relation between Bitcoin and green assets. The corresponding reason can be attributed to both aspects of green transition and dynamics of production costs, and will be further discussed in the next section.

4.3. Time varying impacts of green financial assets and related financial indicators on Bitcoin

Having studied the spillover of Bitcoin price fluctuations on prices of green financial assets and related financial indicators, we investigate the spillover impact from the other direction by using the time-varying IRF produced by the TVP-VAR model with stochastic volatility. Through this, the potentially bi-directional relationship of Bitcoin prices with green financial asset prices and related financial indices is identified. The corresponding results regarding the time-varying Bitcoin price response at different time points in pre- and post-COVID-19 periods are respectively reported in Figures 8 and 9. Specifically, once receiving a unit price shock to green financial assets before the pandemic, as shown in Panel (a) of Figure 8, Bitcoin prices respond positively from zero at the initial stage to shocks from SWI and GCEI, while the impacts of ESGLI and GBI on Bitcoin prices turn negative from zero. The response of Bitcoin prices to the shocks from green financial assets at different time points (i.e., the first-quarter, the half year, and the third-quarter periods) depicts a consistent and overlapping pattern. Moreover, as depicted in Panel (b) of Figure 8, Bitcoin prices demonstrate a consistent response to shocks from all green financial assets before and after the pandemic onset except for GBI. For the latter, it experienced a reversed pattern when facing Bitcoin price shocks before and after the pandemic.

[Figure 8 about here.]

In terms of the Bitcoin price response to a unit shock from related financial indicators, as shown in Figure 9, the responses to shocks from indices of the cryptocurrency market condition from perspectives of price uncertainty (UCRY Price) and environmental sustainability (ICEA) tend to have a similar pattern that evolves from zero at the initial time point, peaks at the short horizons, and then revert to zero within around four horizons. The above responses are highly consistent not only in the face of shocks from different time points (i.e., the first-quarter, the half year, and the third-quarter periods), but also in pre- and post-COVID-19 periods. Moreover, the responses of Bitcoin prices to shocks from both indices of the cryptocurrency market condition from perspectives of policy uncertainty (URCY Policy) and VIX are shown to have different dynamic patterns in the face of shocks from different points. At the same time, the announcement of the pandemic tends to reverse the Bitcoin price response to shocks from URCY Policy and VIX at various time points.

[Figure 9 about here.]

Importantly, as for the contemporaneous price impacts of the four-target green financial assets on Bitcoin, they are shown to be zero and remain consistent before and during the COVID-19 pandemic at different time points (i.e., the first quarter, the half year, and the third quarter) as depicted in Figure 8. The above demonstrates the effective hedging role of green financial assets for Bitcoin. Regarding that of the financial indicators related to the cryptocurrency market condition, indices of VIX, UCRY price, and ICEA consistently depict negative or no significant relationship with Bitcoin before and during the pandemic at different time points, showing as an investment hedge. At the same time, compared to the pre-pandemic period, the impacts of UCRY policy on Bitcoin reverses to be negative after the pandemic onset with relatively large magnitudes. Furthermore, it is worth noting that although being within the same and broad category, different types of green assets could impact Bitcoin differently, and vice versa. This is consistent with the viewpoint that various green assets could result in distinct environmental benefits from green transition, further leading to their different relations with Bitcoin (Naeem and Karim, 2021; Symitsi and Chalvatzis, 2018). In addition, since financialization of green-related projects/investments features different degrees, this might also lead to different relation patterns of various green assets with Bitcoin (Naeem et al., 2021).

Overall, our results are in line with existing findings that green markets provide effective diversification and hedging potential for other financial assets notably including Bitcoin (Naeem et al., 2021; Nguyen et al., 2021; Lucey et al., 2021b). In the light of the extant literature (Chan et al., 2019; Cheah et al., 2022; Dyhrberg, 2016; Grobys, 2021; Liu et al., 2022; Pal and Mitra, 2019), such the sheltering role of green assets can be explained by two underlying mechanisms, i.e., the process of green economic transition, and the dynamics of production costs. In the context of a globally rising energy consumption with large CO2 emissions, the environmental threats have encouraged the finance of cleaner energy, while also calling for green transition of the energy-intensive development mode including Bitcoin trading and mining. Accordingly, although the presence of active Bitcoin trading pursuing for economic profits, green investors would instead adhere to cleaner investments, leading to negligible or even reverse relationship between dynamics of the two types of assets (Naeem and Karim, 2021). At the same time, from the perspective of production costs, it has to be acknowledged that fossil energy is still the major source that drives the economic operation, and the its price along with the electricity price have recently experienced a marked rising due to various reasons such as pandemic recovery, political conflicts, and energy structure adjustment, etc. This would further encourage the usage of renewable and clean energy financed by green projects, while Bitcoin activities would instead encounter higher costs due to the high electricity usage (Le et al., 2021b). Thus, our findings demonstrate the effectiveness of the investment sheltering role of green assets for Bitcoin-related portfolios that inclusion of the former would hedge against the financial risk associated with the latter.

5. Robustness Checks

How robust are our findings to changes in the research design? In this section, we conduct additional analyses to reassure the robustness of our findings in the face of inclusion of the price series of another important cryptocurrency, i.e., Ethereum, replacement of the green asset indices with alternative ones, and changes in the sample period, respectively.

5.1. Inclusion of the Ethereum price series

How sensitive are our obtained results regarding the market interaction between Bitcoin and green assets when considering market dynamics of other leading cryptocurrencies? Our robustness check starts by including the Ethereum price in the empirical estimation. Ethereum is known as the cryptocurrency Ether issued in a decentralized computing platform to reward mining nodes, which is another widely-traded cryptocurrency in addition to Bitcoin (Conlon et al., 2020). Specifically, we re-estimate the market interaction between Bitcoin and green asset by using the TVP-VAR model with the stochastic volatility, while considering the role of Ethereum price.

Overall, as an intuitive illustration through the time-varying impulse response function (IRF) analysis, it is clear that the results are broadly consistent in the estimations with and without considering the Ethereum price.[6] In particular, the IRF plot regarding the Bitcoin – green asset market interaction when considering the Ethereum price before and during the COVID-19 pandemic is exhibited in Figure 10, which results are similar to the corresponding counterparts in the main analysis shown in Figure 5. In terms of the contemporaneous relationship, the response of green financial assets after receiving a unit shock to Bitcoin prices before the pandemic is presented in Panel (a) of Figure 10 where Bitcoin acts as an investment shelter on the specific green financial asset GCEI. During the pandemic, its sheltering role is further enhanced and extended to three green assets, i.e., SWI, ESGLI, and GCEI, as shown in Panel (b) of Figure 10. The dynamic and potentially sheltering role of the Bitcoin price tends to be consistent when the unit shock is impulse in different time points, i.e., the first quarter, the half year, and the third quarter, further demonstrating that our results are not sensitive to inclusion of additional cryptocurrency prices.

[Figure 10 about here.]

5.2. Replacement of green asset indices with alternative ones

To further examine the robustness of our main results regarding the time-varying market dependence of Bitcoin with green financial assets, we follow Ren and Lucey (2021) by considering the WilderHill Clean Energy Index (CEI) to measure the overall performance of clean energy sector. CEI is then used to replace the S&P Global Clean Energy Index (GCEI) in the re-estimation of our TVP-VAR model with stochastic volatility. Our obtained results after the replacement of GCEI by CEI have been visually presented by the time-varying IRF

[6]For each of the following three robustness checks, the IRF results about all the time-varying interactions of Bitcoin prices with green financial asset prices and related financial indices before and during the COVID-19 pandemic are shown to be broadly consistent with our main findings. While the full version of the IRF plots is compressed due to limited space and is available from the authors upon request, we provide some typical illustrations that show the particular market interactions under focus.

plot with the impact of the market dynamics of green assets on that of Bitcoin particularly shown in Figure 11. Overall, the response patterns of the Bitcoin price when receiving a unit shock to each of the four green financial assets shown in Figure 11 generally mimic that of the counterparts in our main findings reported in Figure 8 both before and during the COVID-19 periods. This further supports our argument that the green financial assets are typically regarded as the investment shelter as a (weak) hedge for Bitcoin. Therefore, our results are not sensitive to the variable replacement of the employed green financial assets.

[Figure 11 about here.]

5.3. Changes in the sample period

As an additional robustness check, we conduct a re-estimation by changing the sample period. Following the extant literature (e.g., Conlon et al., 2020; Conlon and McGee, 2020), updated sub-samples before and after the announcement date of the COVID-19 pandemic with the length for each sub-sample being as a whole year, i.e., from 01 March 2019 to 11 March 2020, and from 12 March 2020 to 30 March 2021. It has been checked that the market relationship of Bitcoin with green assets and related financial indicators using the updated subsamples is consistent with that of our main findings. Particularly, the time-varying IRF results for the response of Bitcoin prices in the face of a unit shock to related financial indicators using the updated sub-samples of before and during the pandemic are respectively depicted in Figure 12, being broadly in line with the corresponding counterparts obtained in our main results shown in Figure 9. Importantly, the contemporaneous price impacts of related financial indices on Bitcoin are found to be zero except the positive impact of URCY policy on Bitcoin before the pandemic although its contemporaneous impact turns to be zero during the pandemic. The above speaks in favor of the weak sheltering role of typical and related financial indicators such as VIX, UCRY price, and ICEA for Bitcoin in both the sub-samples of before and during the COVID-19, further reassuring the robustness of our main findings.

[Figure 12 about here.]

6. Conclusions

In the face of rapid climate warming worldwide, the pursuit of future dynamics of the Bitcoin market within a green and sustainable environment has become increasingly important, driving ongoing but still limited attention on whether to add green assets to the Bitcoin-related portfolio for risk diversification while contributing to the green commitment. At the same time, the onset of the COVID-19 pandemic and its associated financial turmoil call for a reinvestigation of the cross-sectional dynamics of the financial markets, among which the connectedness tends to become more correlated during the downturn.

Our paper, therefore, examines the dynamics of the market dependence between Bitcoin and green financial assets over time by applying a recently-developed time-varying parameter VAR (TVP-VAR) model with stochastic volatility. Four indices such as Dow Jones Sustainability World Index (SWI), S&P ESG Leader Index (ESGLI), S&P Green Bond Index (GBI), and S&P Global Clean Energy Index (GCEI) are considered to represent the dynamics of the green assets through four perspectives in a comprehensive manner. The role of two uncertainty indices specifically designed for the cryptocurrency market by Lucey et al. (2021b), along with an index of cryptocurrency environmental attention developed by Lucey et al. (2021a), are particularly considered for accurate interpretation of the Bitcoin market interaction with green asset markets.

Consistent with our expectations, the potential asymmetry of the market dependence is found through three perspectives, i.e., impact directions, time points where the unit shock is being imposed in the IRF (i.e., short-, medium-, and long-runs), as well as before and during the pandemic. The investment sheltering role of Bitcoin/green assets against adverse fluctuations in one another is shown by the contemporaneous market linkage. Specifically, before the pandemic, Bitcoin is found to consistently play a sheltering role of effective hedge on the specific green financial asset GBI at various time horizons as indicated by its negative price impact on GBI. The sheltering role of Bitcoin is further enhanced after the pandemic outbreak that the price of Bitcoin negatively affects that of three out of four green assets under research, i.e., SWI, ESGLI, and GBI, during the pandemic. On the other hand, the four green assets are shown to consistently exhibit an investment shelter as a weak hedge for Bitcoin at different time horizons before and during the pandemic. The robustness of our findings is further reassured by a series of additional analysis.

While it is known that assets tend to become increasingly co-moved during economic downturns (e.g., Bekaert et al., 2009; Goodell and Goutte, 2021b), in the financial turmoil related to the COVID-19 bear market, Bitcoin has depicted its independence with other assets, showing effective investment sheltering role especially against green assets. These findings contribute to the currently-ongoing debate as to whether green assets could act as an investment shelter for the Bitcoin-related portfolio, and offer Bitcoin investors with clear insights for both risk mitigation and green commitment in their portfolios. In turn, comprehension on the underlying investment sheltering role of Bitcoin for green portfolios is also gained. Therefore, our findings are important for not only hedging against green portfolios but also seeking green shelter. The findings also help policymakers promote the green and sustainable development of the financial market, notably the Bitcoin market, effectively combating global climate change

References

Aloui, D., Goutte, S., Guesmi, K., Hchaichi, R., 2020. Covid 19's impact on crude oil and natural gas s&p gs indexes .

Baur, D.G., Dimpfl, T., Kuck, K., 2018. Bitcoin, gold and the us dollar–a replication and extension. Finance research letters 25, 103–110.

Bekaert, G., Hodrick, R.J., Zhang, X., 2009. International stock return comovements. The Journal of Finance 64, 2591–2626.

Bouri, E., Das, M., Gupta, R., Roubaud, D., 2018. Spillovers between bitcoin and other assets during bear and bull markets. Applied Economics 50, 5935–5949.

Bouri, E., Gil-Alana, L.A., Gupta, R., Roubaud, D., 2019. Modelling long memory volatility in the bitcoin market: Evidence of persistence and structural breaks. International Journal of Finance & Economics 24, 412–426.

Chan, J.C., Eisenstat, E., 2018. Bayesian model comparison for time-varying parameter vars with stochastic volatility. Journal of Applied Econometrics 33, 509–532.

Chan, W.H., Le, M., Wu, Y.W., 2019. Holding bitcoin longer: The dynamic hedging abilities of bitcoin. The Quarterly Review of Economics and Finance 71, 107–113.

Cheah, J.E.T., Luo, D., Zhang, Z., Sung, M.C., 2022. Predictability of bitcoin returns. The European Journal of Finance 28, 66–85.

Chen, J., Zhu, X., Li, H., 2020. The pass-through effects of oil price shocks on china's inflation: A time-varying analysis. Energy Economics 86, 104695.

Clark, T.E., Ravazzolo, F., 2015. Macroeconomic forecasting performance under alternative specifications of time-varying volatility. Journal of Applied Econometrics 30, 551–575.

Cogley, T., Sargent, T.J., 2001. Evolving post-world war ii us inflation dynamics. NBER macroeconomics annual 16, 331–373.

Cogley, T., Sargent, T.J., 2005. Drifts and volatilities: monetary policies and outcomes in the post wwii us. Review of Economic dynamics 8, 262–302.

Conlon, T., Corbet, S., McGee, R.J., 2020. Are cryptocurrencies a safe haven for equity markets? an international perspective from the covid-19 pandemic. Research in International Business and Finance 54, 101248.

Conlon, T., McGee, R., 2020. Safe haven or risky hazard? bitcoin during the covid-19 bear market. Finance Research Letters 35, 101607.

Corbet, S., Lucey, B., Yarovaya, L., 2021. Bitcoin-energy markets interrelationships-new evidence. Resources Policy 70, 101916.

D'Agostino, A., Gambetti, L., Giannone, D., 2013. Macroeconomic forecasting and structural change. Journal of applied econometrics 28, 82–101.

Duan, K., Li, Z., Urquhart, A., Ye, J., 2021a. Dynamic efficiency and arbitrage potential in bitcoin: A long-memory approach. International Review of Financial Analysis 75, 101725.

Duan, K., Ren, X., Shi, Y., Mishra, T., Yan, C., 2021b. The marginal impacts of energy prices on carbon price variations: evidence from a quantile-on-quantile approach. Energy Economics 95, 105131.

Dyhrberg, A.H., 2016. Hedging capabilities of bitcoin. is it the virtual gold? Finance Research Letters 16, 139–144.

Goodell, J.W., 2020. Covid-19 and finance: Agendas for future research. Finance Research Letters 35, 101512.

Goodell, J.W., Goutte, S., 2021a. Co-movement of covid-19 and bitcoin: Evidence from wavelet coherence analysis. Finance Research Letters 38, 101625.

Goodell, J.W., Goutte, S., 2021b. Diversifying equity with cryptocurrencies during covid-19. International Review of Financial Analysis 76, 101781.

Grobys, K., 2021. When bitcoin has the flu: On bitcoin's performance to hedge equity risk in the early wake of the covid-19 outbreak. Applied Economics Letters 28, 860–865.

Hartmann, P., Straetmans, S., Vries, C.d., 2004. Asset market linkages in crisis periods. Review of Economics and Statistics 86, 313–326.

Huang, Y., Duan, K., Mishra, T., 2021. Is bitcoin really more than a diversifier? a pre-and post-covid-19 analysis. Finance Research Letters , 102016.

Kapar, B., Olmo, J., 2019. An analysis of price discovery between bitcoin futures and spot markets. Economics Letters 174, 62–64.

Kwon, J.H., 2020. Tail behavior of bitcoin, the dollar, gold and the stock market index. Journal of International Financial Markets, Institutions and Money 67, 101202.

Le, L.T.N., Yarovaya, L., Nasir, M.A., 2021a. Did covid-19 change spillover patterns between fintech and other asset classes? Research in International Business and Finance , 101441.

Le, T.L., Abakah, E.J.A., Tiwari, A.K., 2021b. Time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution. Technological Forecasting and Social Change 162, 120382.

Lee, S.C., Lin, C.T., Yang, C.K., 2011. The asymmetric behavior and procyclical impact of asset correlations. Journal of Banking & Finance 35, 2559–2568.

Liu, Y., Tsyvinski, A., Wu, X., 2022. Common risk factors in cryptocurrency. The Journal of Finance 77, 1133–1177.

Lucey, B.M., Vigne, S., Wang, Y., Yarovaya, L., 2021a. An index of cryptocurrency environmental attention (icea). Available at SSRN 3866535 .

Lucey, B.M., Vigne, S.A., Yarovaya, L., Wang, Y., 2021b. The cryptocurrency uncertainty index. Finance Research Letters , 102147.

Maghyereh, A., Abdoh, H., 2020. Tail dependence between bitcoin and financial assets: Evidence from a quantile cross-spectral approach. International Review of Financial Analysis 71, 101545.

Naeem, M.A., Karim, S., 2021. Tail dependence between bitcoin and green financial assets. Economics Letters 208, 110068.

Naeem, M.A., Mbarki, I., Alharthi, M., Omri, A., Shahzad, S.J.H., 2021. Did covid-19 impact the connectedness between green bonds and other financial markets? evidence from time-frequency domain with portfolio implications. Frontiers in Environmental Science 9, 657533.

Nakajima, J., et al., 2011. Time-varying parameter var model with stochastic volatility: An overview of methodology and empirical applications .

Nguyen, T.T.H., Naeem, M.A., Balli, F., Balli, H.O., Vo, X.V., 2021. Time-frequency comovement among green bonds, stocks, commodities, clean energy, and conventional bonds. Finance Research Letters 40, 101739.

Okorie, D.I., 2021. A network analysis of electricity demand and the cryptocurrency markets. International Journal of Finance & Economics 26, 3093–3108.

Pal, D., Mitra, S.K., 2019. Hedging bitcoin with other financial assets. Finance Research Letters 30, 30–36.

Primiceri, G.E., 2005. Time varying structural vector autoregressions and monetary policy. The Review of Economic Studies 72, 821–852.

Rehman, M.U., Kang, S.H., 2021. A time–frequency comovement and causality relationship between bitcoin hashrate and energy commodity markets. Global Finance Journal 49, 100576.

Ren, B., Lucey, B.M., 2021. A clean, green haven?-examining the relationship between clean energy, clean and dirty cryptocurrencies. Examining the Relationship between Clean Energy, Clean and Dirty Cryptocurrencies (November 15, 2021) .

Ren, X., Wang, R., Duan, K., Chen, J., 2022. Dynamics of the sheltering role of bitcoin against crude oil market crash with varying severity of the covid-19: A comparison with gold. Research in International Business and Finance , 101672.

Shahzad, S.J.H., Bouri, E., Roubaud, D., Kristoufek, L., Lucey, B., 2019. Is bitcoin a better safe-haven investment than gold and commodities? International Review of Financial Analysis 63, 322–330.

Sharif, A., Aloui, C., Yarovaya, L., 2020. Covid-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the us economy: Fresh evidence from the wavelet-based approach. International Review of Financial Analysis 70, 101496.

Symitsi, E., Chalvatzis, K.J., 2018. Return, volatility and shock spillovers of bitcoin with energy and technology companies. Economics Letters 170, 127–130.

Urquhart, A., Zhang, H., 2019. Is bitcoin a hedge or safe haven for currencies? an intraday analysis. International Review of Financial Analysis 63, 49–57.

Wang, P., Zhang, H., Yang, C., Guo, Y., 2021. Time and frequency dynamics of connectedness and hedging performance in global stock markets: Bitcoin versus conventional hedges. Research in International Business and Finance , 101479.

Wu, C.C., Ho, S.L., Wu, C.C., 2022. The determinants of bitcoin returns and volatility: Perspectives on global and national economic policy uncertainty. Finance Research Letters 45, 102175.

Yarovaya, L., Brzeszczynski, J., Goodell, J.W., Lucey, B.M., Lau, C.K., 2020. Rethinking financial contagion: Information transmission mechanism during the covid-19 pandemic. Available at SSRN 3602973 .

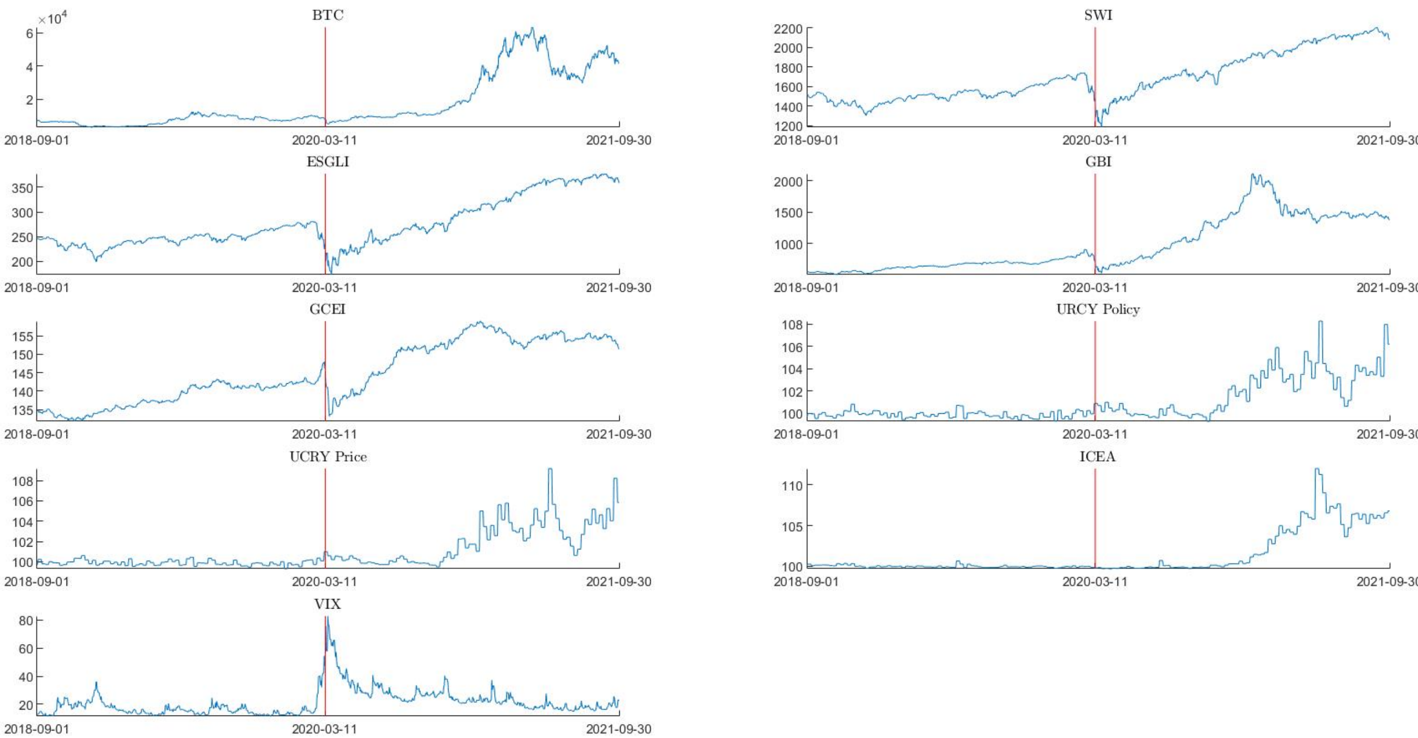


Figure 1: ***Dynamics of target factors over time***

Note: This figure plots the time-varying dynamics of nine target series under research including the Bitcoin price (BTC), four green financial assets (i.e., SWI, ESGLI, GBI, and GCEI), three indices describing the cryptocurrency market condition through both perspectives of uncertainty (i.e., URCY policy and URCY price) and environmental sustainability (ICEA), and the CBOE Volatility Index (VIX).

Figure 2: ***Time-varying posterior estimates for autoregressive coefficients β_t before the COVID-19 pandemic***

Note: This figure reports the time-varying dynamics of the posterior estimates of β_t defined in Equation (3) before the pandemic. Sub-figures on left two columns show the dynamic impacts of Bitcoin prices on prices of green assets (i.e., SWI, ESGLI, GBI, and GCEI) and related financial indicators (i.e., UCRY policy, UCRY price, ICEA, and VIX) over time. Conversely, the ones on right two columns show the response of Bitcoin when facing impacts from green assets and related financial indicators over time. In each sub-figure, the blue solid line stands for the time-varying dynamics of the posterior mean of β_t, and the red dotted lines denote dynamics of the corresponding 95% intervals. The x-axis denotes time periods, and the y-axis denotes the impact magnitude.

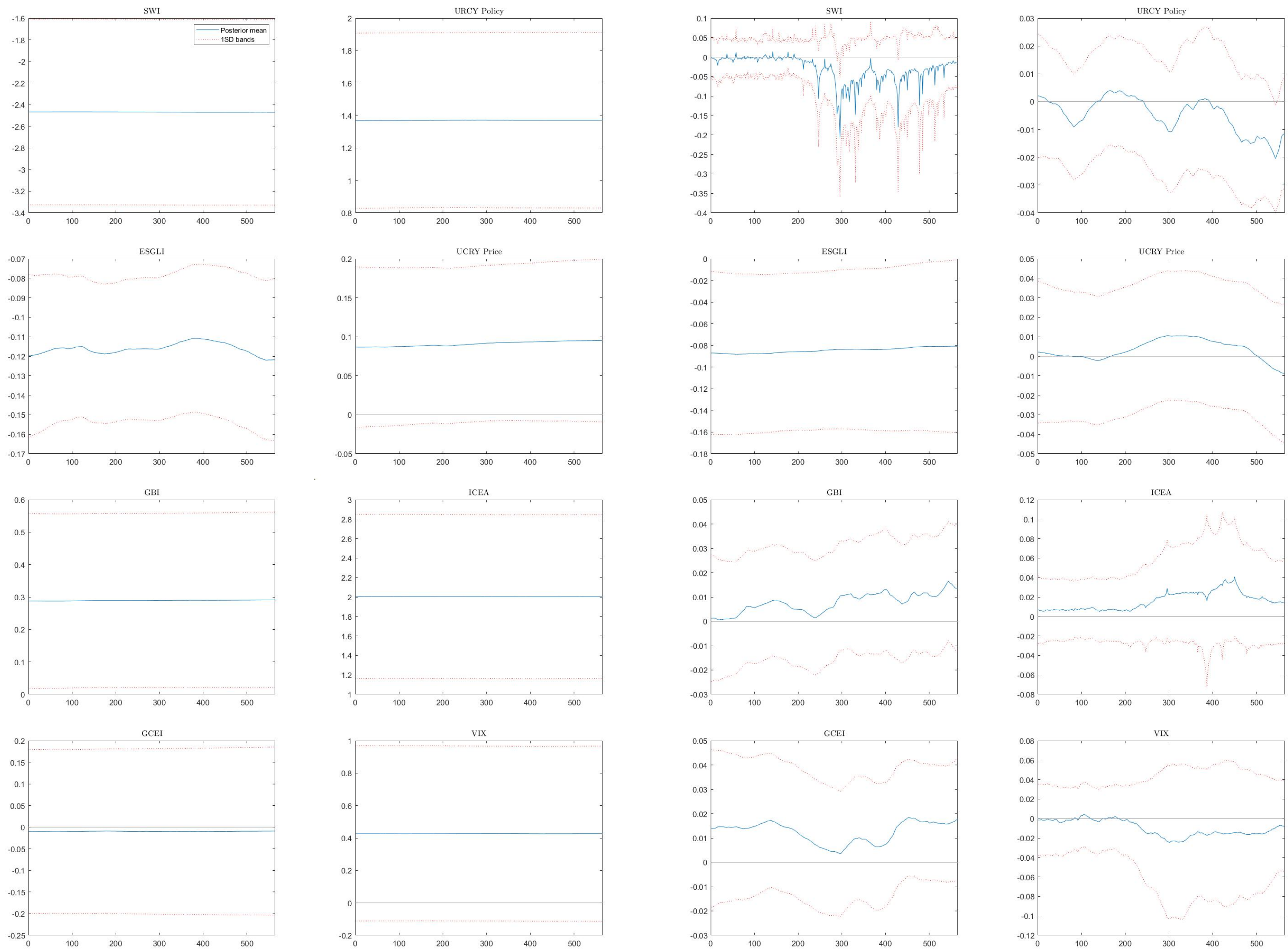


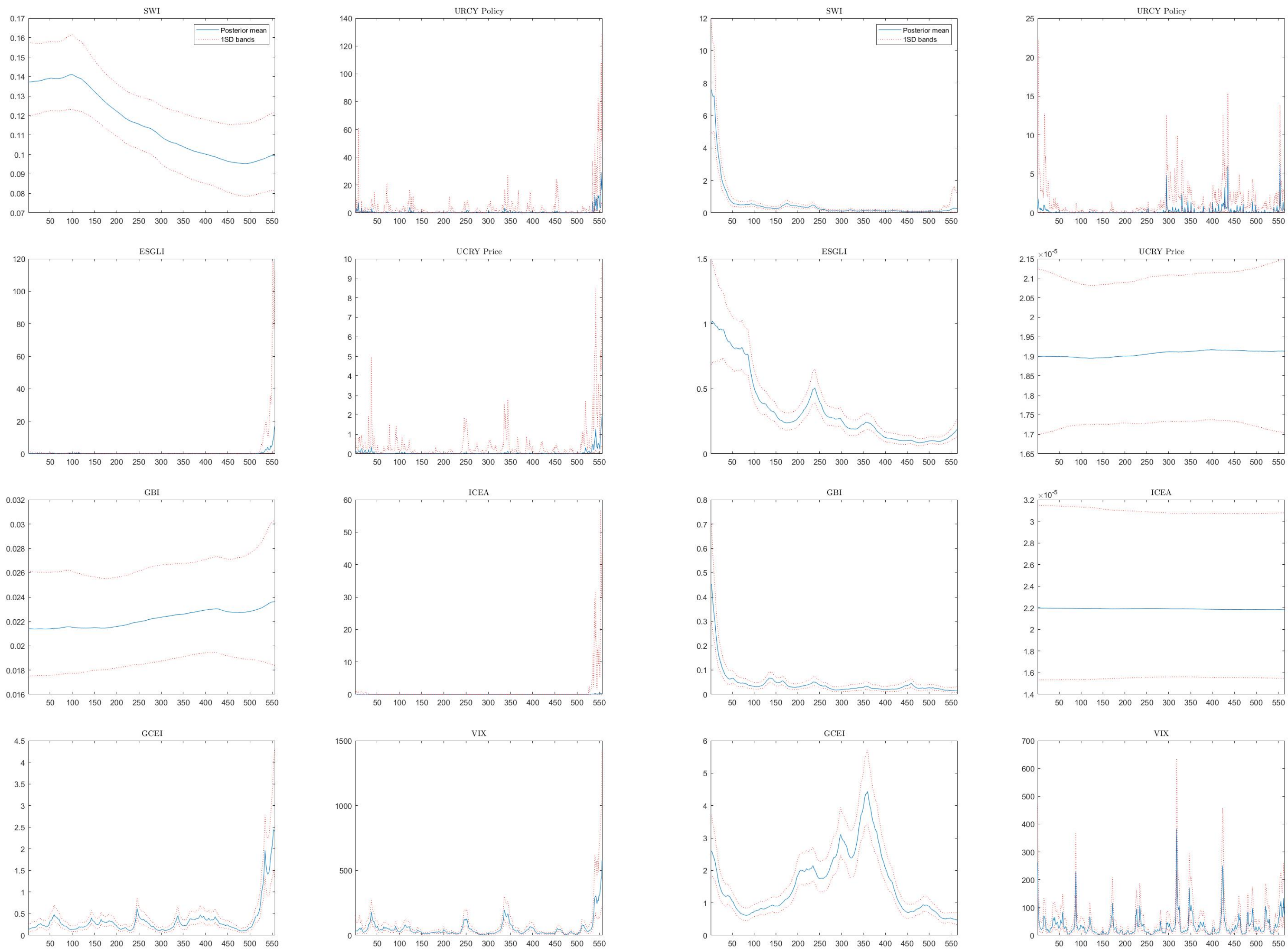
Figure 3: ***Time-varying posterior estimates for autoregressive coefficients β_t in during the COVID-19 pandemic***

Note: This figure reports the time-varying dynamics of the posterior estimates of β_t defined in Equation (3) during the pandemic. Sub-figures on left two columns show the dynamic impacts of Bitcoin prices on prices of green assets (i.e., SWI, ESGLI, GBI, and GCEI) and related financial indicators (i.e., UCRY policy, UCRY price, ICEA, and VIX) over time. Conversely, the ones on right two columns show the response of Bitcoin when facing impacts from green assets and related financial indicators over time. In each sub-figure, the blue solid line stands for the time-varying dynamics of the posterior mean of β_t, and the red dotted lines denote dynamics of the corresponding 95% intervals. The x-axis denotes time periods, and the y-axis denotes the impact magnitude.

(a) *Pre-COVID-19 period* **(b)** *Post-COVID-19 period*

Figure 4: *Time-varying posterior estimates for covariance parameters a_t before and during the COVID-19 pandemic*

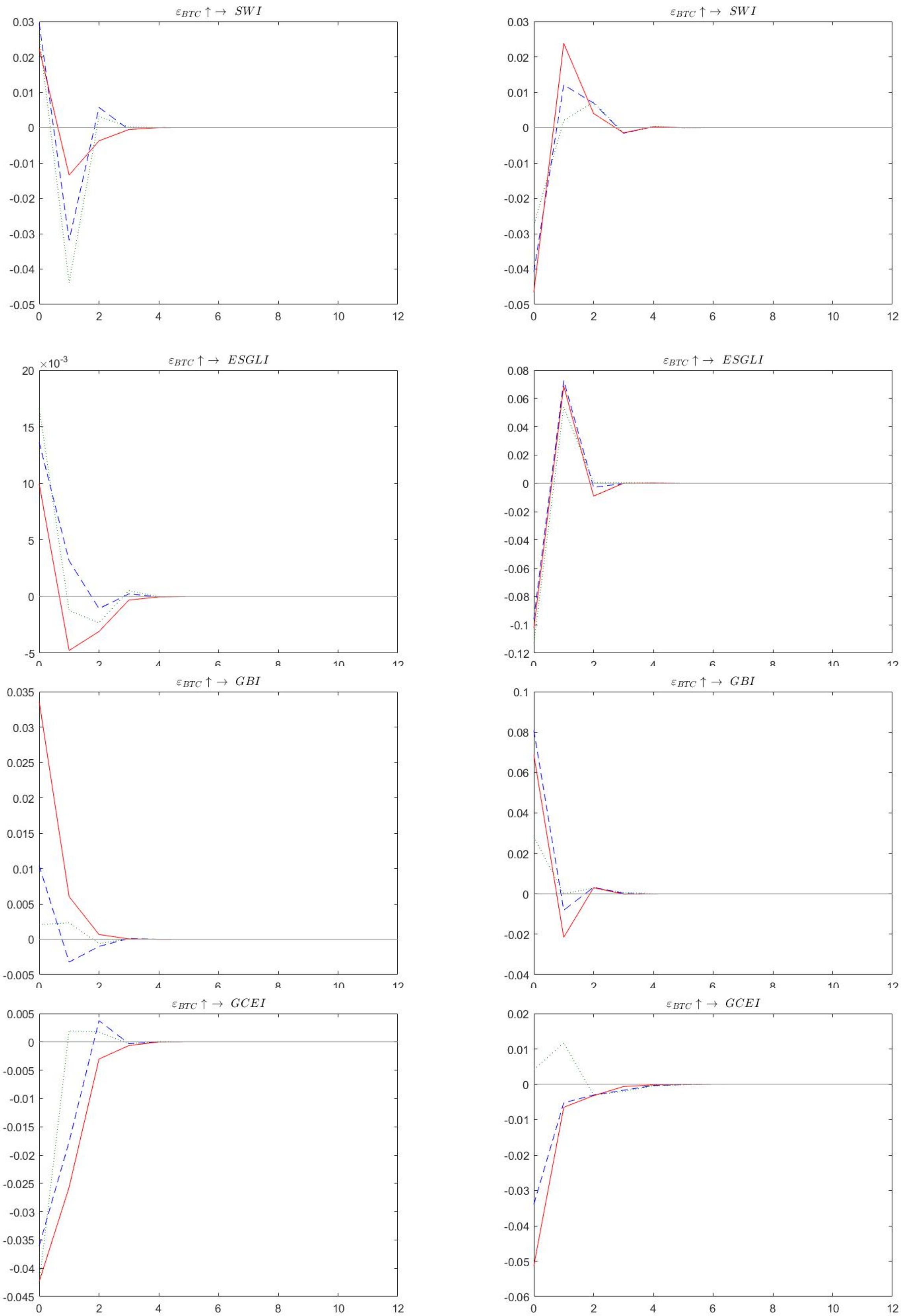
Note: This figure reports the time-varying dynamics of the posterior estimates of t defined in Equation (4). The estimated covariance parameters (i.e., t) of Bitcoin prices with green asset prices and related financial indicators before and during the pandemic are shown in panels (a) and (b), respectively. In each sub-figure, the blue solid line stands for the time-varying dynamics of the posterior mean of β_t, and the red dotted lines denote dynamics of the corresponding 95% intervals. The x-axis denotes time periods, and the y-axis denotes the impact magnitude.



(a) *Pre-COVID-19 period* **(b)** *Post-COVID-19 period*

Figure 5: ***Time-varying posterior estimates for volatility parameters σ_t^2 in the pre- and post-COVID-19 periods***

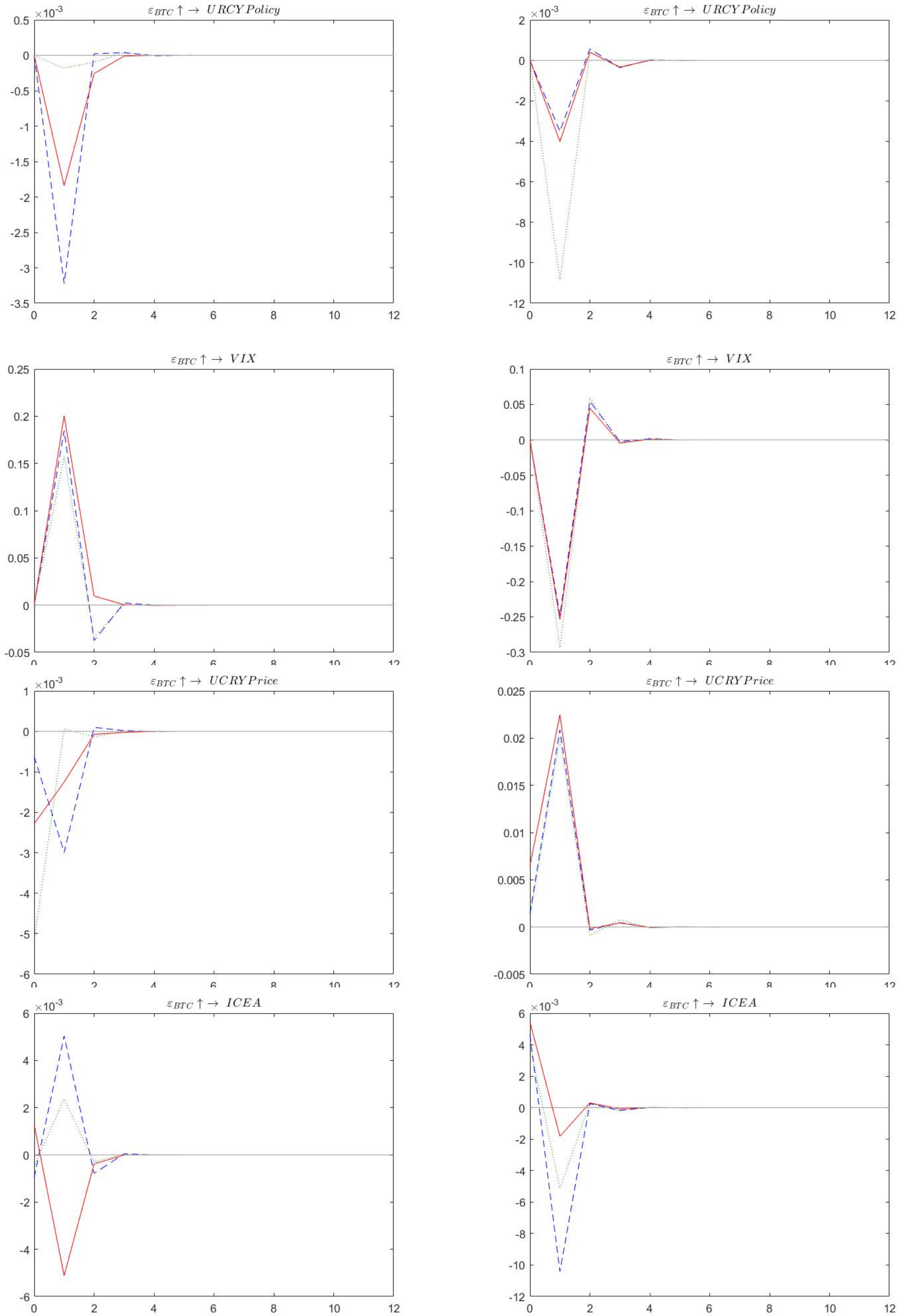
Note: This figure reports the time-varying dynamics of the posterior estimates of σ_t^2 defined in Equation (5). The estimated volatility parameters (i.e., σ_t^2) of each of the considered series before and during the pandemic are shown in panels (a) and (b), respectively. In each sub-figure, the blue solid line stands for the time-varying dynamics of the posterior mean of β_t, and the red dotted lines denote dynamics of the corresponding 95% intervals. The x-axis denotes time periods, and the y-axis denotes the impact magnitude.



(a) *Pre-COVID-19 period* **(b)** *Post-COVID-19 period*

Figure 6: ***The time-varying impulse response of green financial asset prices to a unit shock of Bitcoin prices in the pre- and post-COVID-19 periods***

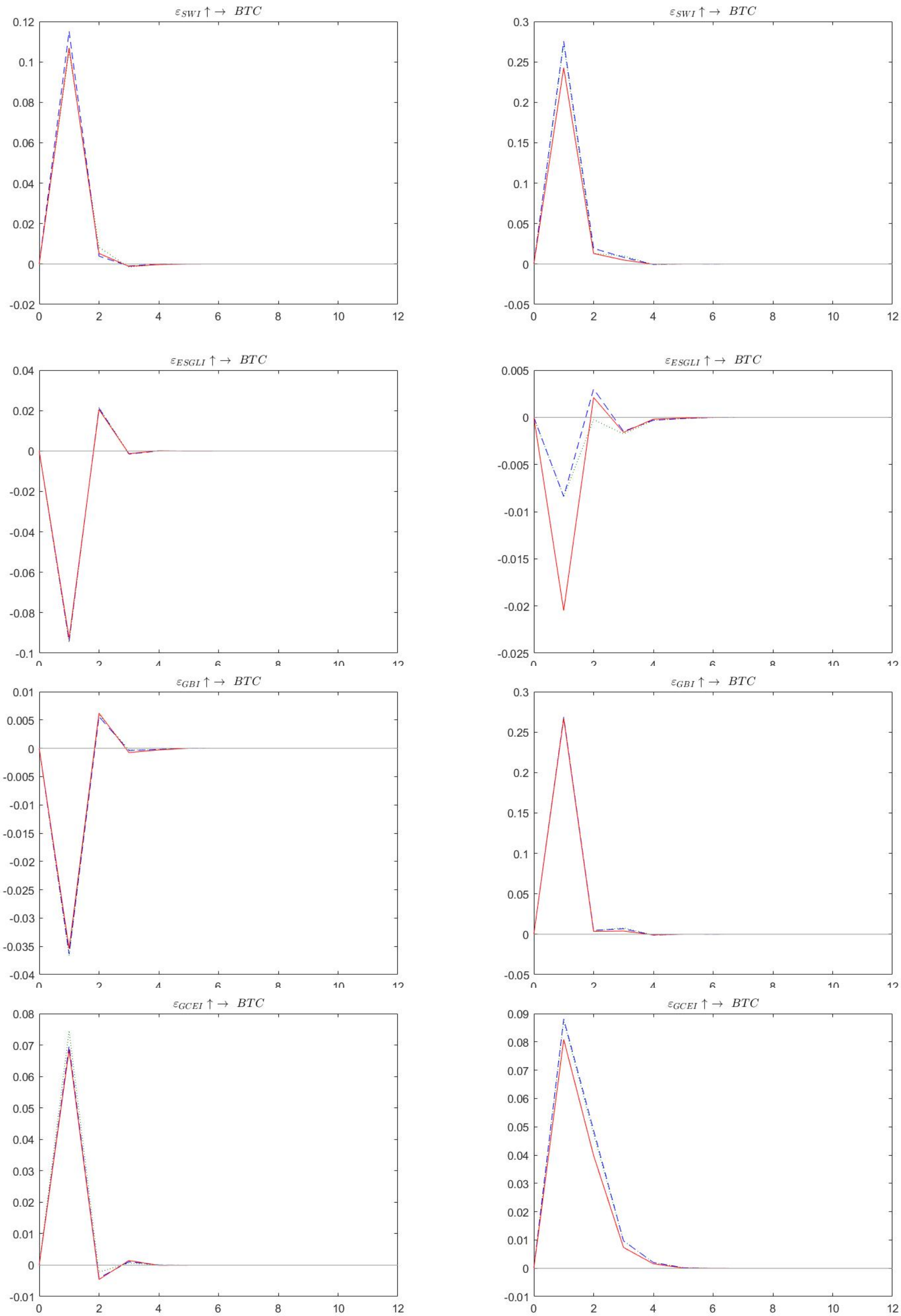
Note: This figure shows the IRF plots before and during the pandemic as shown in panels (a) and (b), respectively. The gray dotted line, blue dashed line, and red solid line refer to the response of the specific green asset when facing a unit shock to Bitcoin prices at different time points, i.e., the first quarter, the half year, and the third quarter, respectively.



(a) *Pre-COVID-19 period* **(b)** *Post-COVID-19 period*

Figure 7: ***The time-varying impulse response of related financial indicators to a unit shock of Bitcoin prices in the pre- and post-COVID-19 periods***

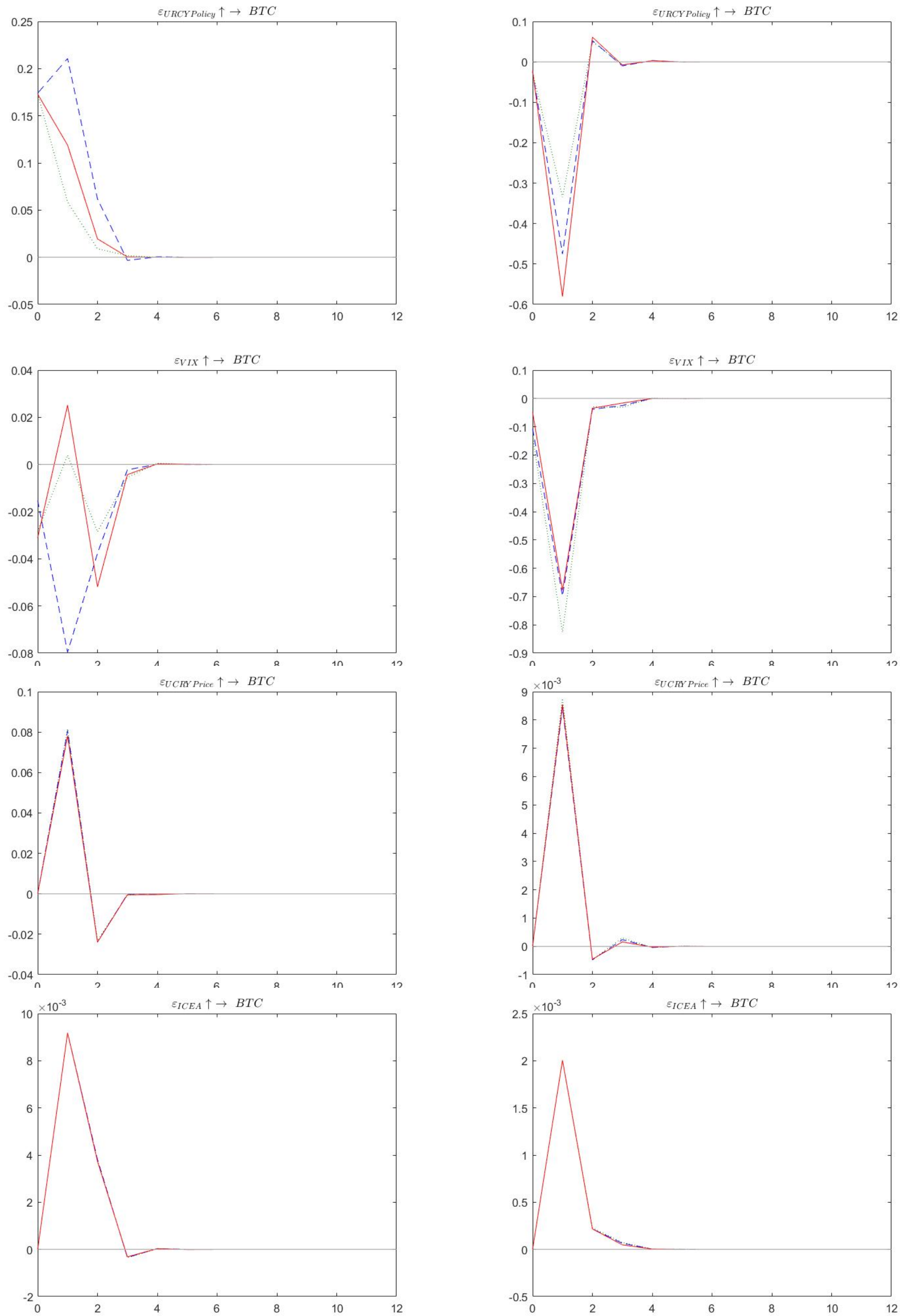
Note: This figure shows the IRF plots before and during the pandemic as shown in panels (a) and (b), respectively. The gray dotted line, blue dashed line, and red solid line refer to the response of the specific related financial indicator when facing a unit shock to Bitcoin prices at different time points, i.e., the first quarter, the half year, and the third quarter, respectively.



(a) *Pre-COVID-19 period* **(b)** *Post-COVID-19 period*

Figure 8: ***The time-varying impulse response of Bitcoin prices to unit shocks of green financial asset prices in the pre- and post-COVID-19 periods***

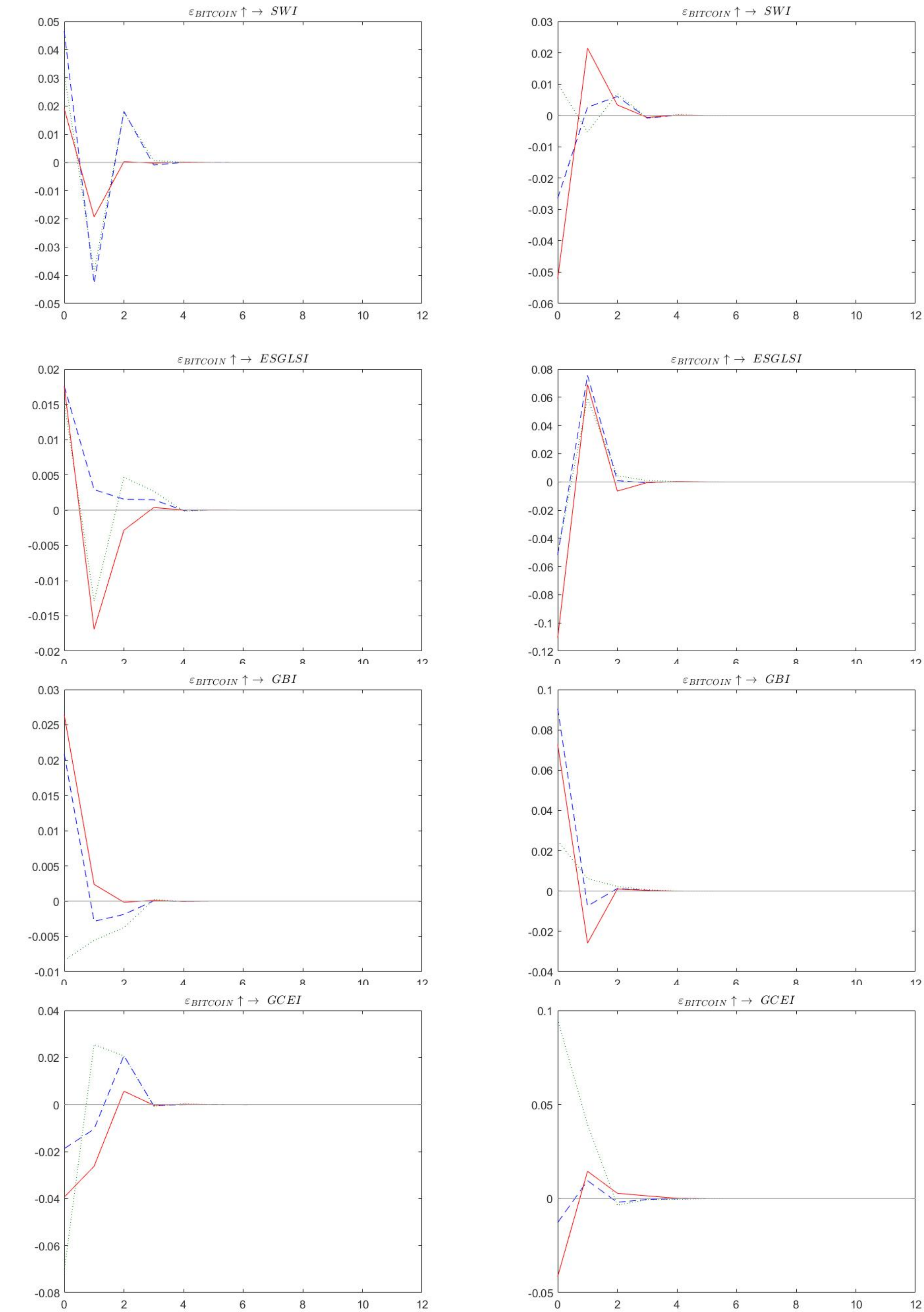
Note: This figure shows the IRF plots before and during the pandemic as shown in panels (a) and (b), respectively. The gray dotted line, blue dashed line, and red solid line refer to the response of the Bitcoin price when facing a unit shock to the price of the specific green asset at different time points, i.e., the first quarter, the half year, and the third quarter, respectively.



(a) *Pre-COVID-19 period* **(b)** *Post-COVID-19 period*

Figure 9: ***The time-varying impulse response of Bitcoin prices to unit shocks of related financial indicators in the pre- and post-COVID-19 periods***

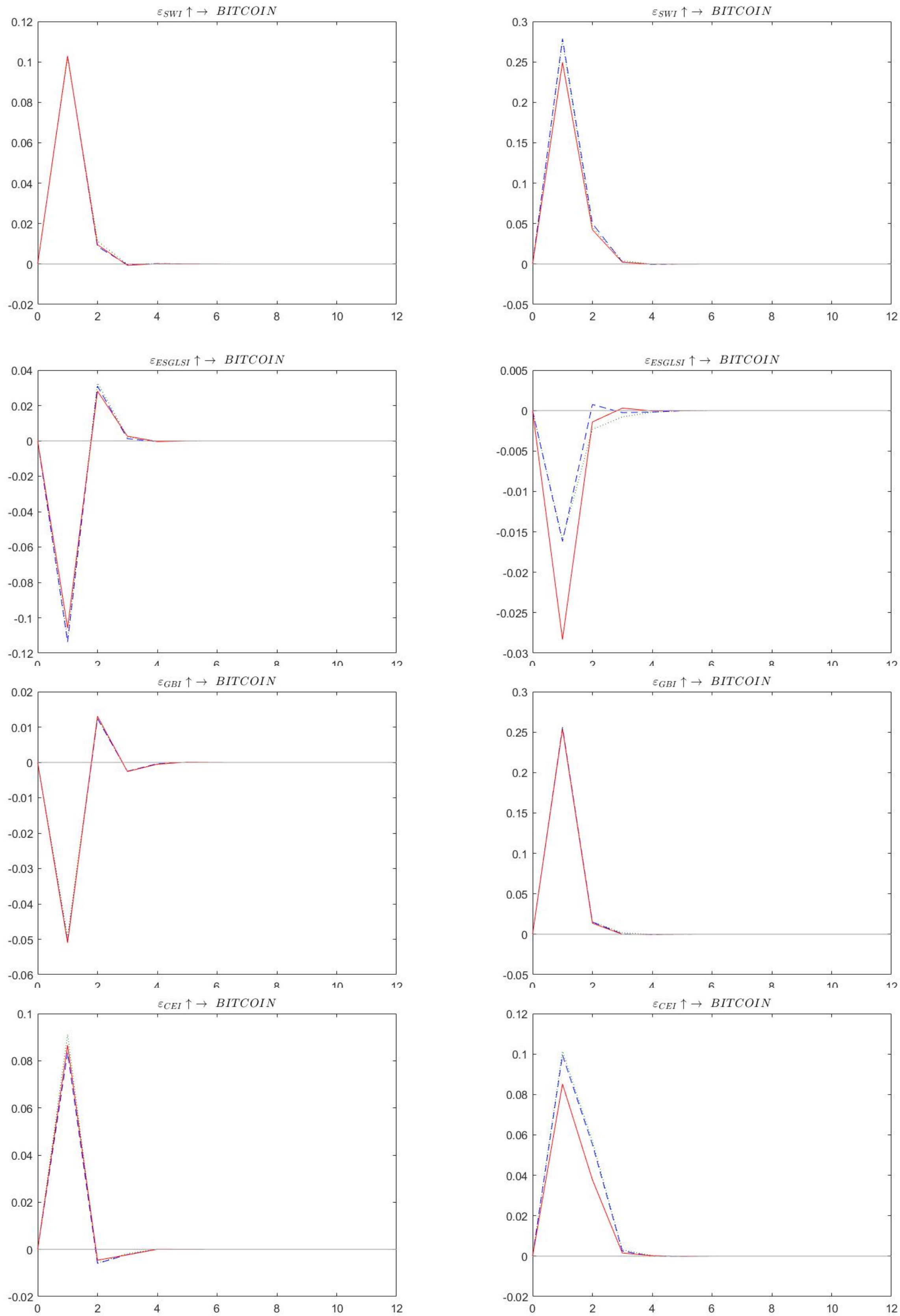
Note: This figure shows the IRF plots before and during the pandemic as shown in panels (a) and (b), respectively. The gray dotted line, blue dashed line, and red solid line refer to the response of the Bitcoin price when facing a unit shock to the related financial indicator at different time points, i.e., the first quarter, the half year, and the third quarter, respectively.



(a) *Pre-COVID-19 period* **(b)** *Post-COVID-19 period*

Figure 10: ***Robustness 1: IRF plots of green asset prices to a unit shock of Bitcoin prices in the pre- and post-COVID-19 when including the Ethereum prices***

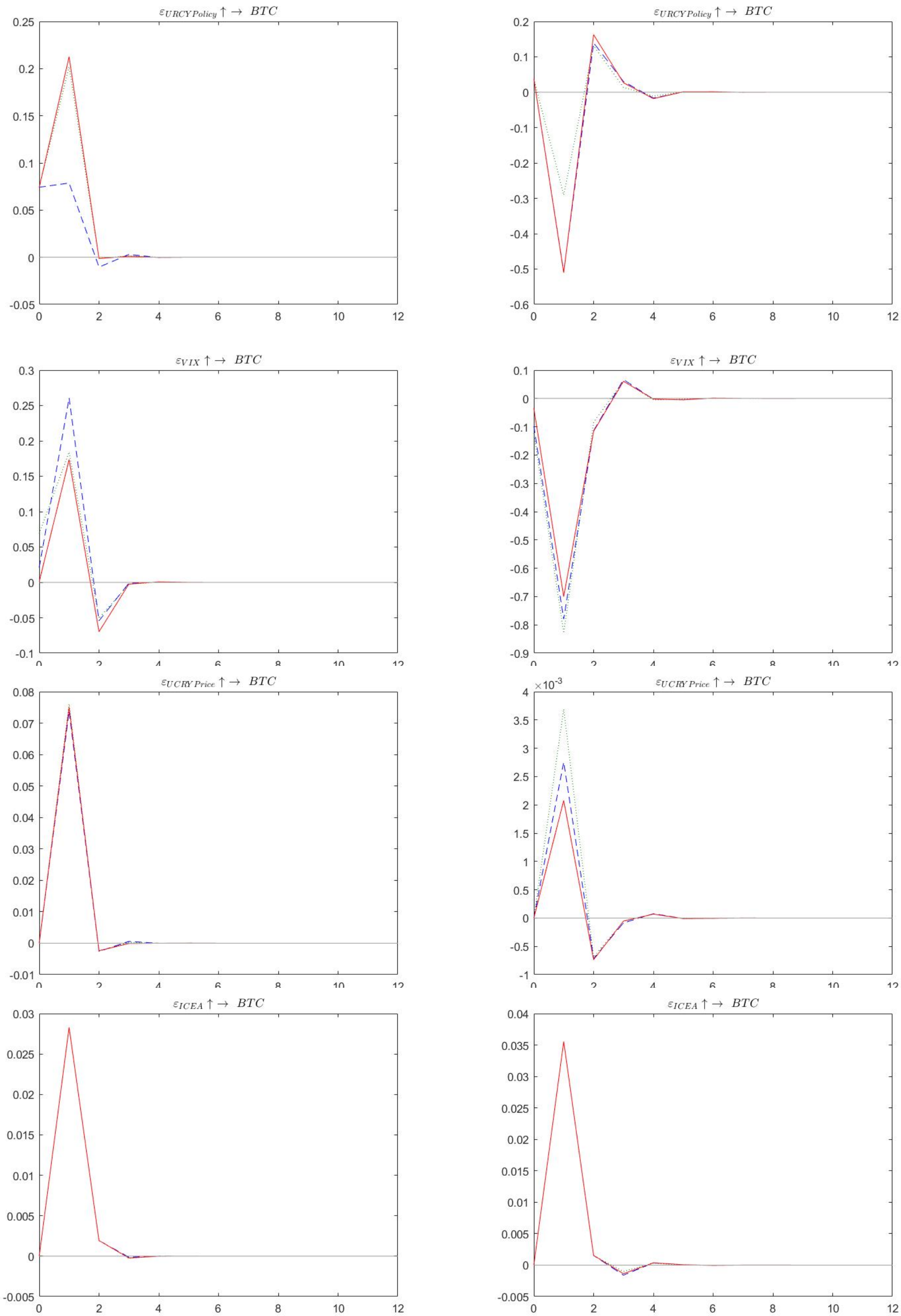
Note: This figure shows the IRF plots before and during the pandemic as shown in panels (a) and (b), respectively. The gray dotted line, blue dashed line, and red solid line refer to the response of the specific variable when facing a unit shock to Bitcoin prices at different time points, i.e., the first quarter, the half year, and the third quarter, respectively.



(a) *Pre-COVID-19 period* **(b)** *Post-COVID-19 period*

Figure 11: ***Robustness 2: IRF plots of Bitcoin prices to a unit shock of green asset prices in the pre- and post-COVID-19 with alternative green asset prices***

Note: This figure shows the IRF plots before and during the pandemic as shown in panels (a) and (b), respectively. The gray dotted line, blue dashed line, and red solid line refer to the response of the specific variable when facing a unit shock to a target green asset at different time points, i.e., the first quarter, the half year, and the third quarter, respectively.



(a) *Pre-COVID-19 period* **(b)** *Post-COVID-19 period*

Figure 12: ***Robustness 3: IRF plots of Bitcoin prices to a unit shock of related financial indicators in the pre- and post-COVID-19 with changes in the sample period***

Note: This figure shows the IRF plots before and during the pandemic as shown in panels (a) and (b), respectively. The gray dotted line, blue dashed line, and red solid line refer to the response of the specific variable when facing a unit shock to a target related financial indicator at different time points, i.e., the first quarter, the half year, and the third quarter, respectively.

Table 1: *Descriptive statistics*

	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Panel A: Pre-Covid-19						
BTC	0.0222	3.5610	-14.9442	15.2987	-0.1216	3.6718
SWI	-0.0295	0.8499	-10.6051	2.8620	-4.5717	49.5546
ESGLSI	-0.0368	1.0774	-10.8401	4.4731	-2.8730	26.4139
GBI	0.0098	0.2101	-2.3671	0.8167	-2.3432	30.2399
GCEI	0.0177	1.1340	-12.4971	5.5528	-4.1089	43.9267
UCRY Policy	0.0022	0.1295	-0.9091	0.9041	0.2036	18.3164
UCRY Price	0.0021	0.1519	-1.1347	1.0598	0.3207	21.1604
ICEA	-0.0006	0.0611	-0.4383	0.7623	2.7226	57.5845
VIX	0.3171	7.2506	-19.8144	38.2167	1.3691	5.5387
Panel B: Post-Covid-19						
BTC	0.3473	3.7728	-13.4276	16.1041	0.1385	1.8977
SWI	0.0754	0.9812	-8.7034	7.6939	-0.5779	21.2194
ESGLSI	0.0883	1.4428	-12.9915	11.2908	-0.5905	21.8781
GBI	0.0124	0.2861	-2.4099	2.0127	-0.8740	15.6212
GCEI	0.1366	1.8595	-10.5579	11.0330	-0.2783	6.9841
UCRY Policy	0.0091	0.4410	-3.5751	4.4182	2.0752	37.0057
UCRY Price	0.0083	0.4646	-3.2736	3.9308	2.7952	35.0517
ICEA	0.0120	0.3533	-2.3672	5.6834	6.4870	127.4807
VIX	-0.1618	6.7453	-20.8405	48.0214	1.6034	9.2081

Note: This table provides descriptive statistics of the variables used in this study, including the price series of Bitcoin (BTC), the four green financial assets, i.e., SWI, ESGLSI, GBI, GCEI, the two uncertainty index of the cryptocurrency market through aspects of policy and price, i.e., UCRY policy and UCRY price, the index of Cryptocurrency Environmental Attention (ICEA), and the CBOE Volatility Index (VIX).