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The impact of central bank digital currency news on the stock and cryptocurrency markets: Evidence from the TVP-VAR model

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ABSTRACT

This study employs a non-linear framework to investigate the impacts of central bank digital currency (CBDC) news on the financial and cryptocurrency markets. The time-varying vector autoregressive (TVP-VAR) model developed by Primiceri (2005) is estimated based on weekly data from the first week of January 2015 to the last week of December 2021. The vector of endogenous variables in the VAR estimation contains the Central Bank Digital Currency uncertainty index (CBDCU), cryptocurrency policy uncertainty index, S&P 500 index, VIX, and Bitcoin price. The TVP-VAR model's time-varying responses demonstrated that the reactions of the cryptocurrency market to central bank digital currency announcements vary remarkably over time. The impacts of the CBDC shocks on the financial market have been increasingly visible during the COVID-19 pandemic. According to the time-varying forecast error decompositions, CBDCU and VIX shocks have accounted for most of the variance in cryptocurrency uncertainty and Bitcoin return shocks, notably during the COVID-19 period.

1. Introduction

Smart technologies are rapidly shifting people's lifestyles. The new digital economy requires a digital currency, hence the increasing use of the terms "cashless city" and "cashless economy". Because of the increasing digitization of the global financial system, a Central Bank Digital Currency (CBDC) is required to serve as a form of digital asset. This can play a crucial role in ensuring financial stability, constructing a better payment system, enhancing monetary policy (Sissoko, 2020; McLaughlin, 2021; Soderberg et al., 2022), establishing a new monetary era (Wang et al., 2022), and supporting unconventional monetary policy (Bordo and Levin, 2017). Cukierman (2019) asserts that in an era of rapid issuance of private digital currencies, monetary authorities will have no choice but to issue their digital currencies to maintain an effective monetary policy. A recent survey by BIS showed that 9 out of 10 monetary

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authorities are currently examining CBDCs, while more than half are developing a CBDC.[4] Allen et al. (2022) argue that introducing the Chinese e-CNY could solve some inherent problems (e.g., lack of transparency, inefficiency, centralized control, and high costs) in traditional financial systems. CBDCs thus represent a significant innovation in money and banking history, which may fundamentally shift the architecture of financial systems while creating a universally accessible central bank (Fernández-Villaverde et al., 2021).

The recent literature on CBDCs has focused on its technological perspective; the conceptual framework, definition, and types of CBDCs; its security and privacy challenges; the impact of CBDCs on the banking system; and issues related to the central bank and monetary policy. Most of these previous studies of digital currencies like CBDCs have been either theoretical or used traditional models, such as VAR and SVAR. For instance, Lucey et al. (2022) built three cryptocurrency indicators to examine the effect of these indices on the financial market using the VAR model. Wang et al. (2022) developed a new CBDC Uncertainty Index (CBDCU) and CBDC Attention Index (CBDCA) and investigated their impact on financial markets using the SVAR model and DCC-GARCH model. This new CBDCs index was derived by counting the occurrence of words related to CBDCs using multiple searches in LexisNexis News and Business, based on more than six hundred million news items since January 2015, when Ecuador launched the first CBDC. Further, Scharnowski (2022) examined cryptocurrency investors' reactions to central bank CBDC speeches using a fixed-effects model. It is concluded that cryptocurrency markets react asymmetrically to the CBDC speeches.

In light of this, our study aims to contribute to the CBDC literature in two respects. First, prior research, except for Wang et al. (2022, 2023) and Scharnowski (2022), has examined theoretical aspects of CBDC adoption. Second, our paper uses a more appropriate and sophisticated empirical approach to study the impact of CBDCs on financial markets. For this purpose, the TVP-VAR model with stochastic volatility developed by Primiceri (2005) is estimated based on weekly data from January 2015 to December 2021 to reveal how CBDC news indices affect the financial and cryptocurrency markets. The CBDC indices are constructed by Wang et al. (2022) to cover over 660 million news stories from LexisNexis News and Business. It thus allows us to examine the effects of CBDC news reports on the financial markets. Furthermore, the TVP-VAR model utilized in this research offers a particular advantage over other non-linear models. The evolution of parameters and error terms over time allows us to capture both gradual and unanticipated changes in the financial markets. Consequently, the TVP-VAR model findings enable decision-makers and society to grasp better the potential benefits and hazards of deploying CBDCs and how they vary based on different technological and economical design choices.

The time-varying responses and forecast error decompositions computed from the TVP-VAR model reveal that the direction and significance of the responses to CBDCU shocks evolve significantly over time. More specifically, the time-varying impact of CBDCU shocks on the financial market has increased, particularly during the period of the COVID-19 pandemic. In line with the time-varying responses, the time-varying forecast error decompositions demonstrate that CBDCU and VIX shocks have explained most of the fluctuations in cryptocurrency uncertainty and Bitcoin return shocks during the COVID-19 period.

The remainder of this paper is structured as follows. Section 2 reviews the CBDC literature. Section 3 describes the data and presents the methodology. The empirical findings are discussed in Section 4. Finally, Section 5 offers some concluding remarks.

2. Literature Review

CBDCs are a form of virtual currency, but they differ from the numerous types of private digital currencies (cryptocurrencies), whose repeated price bubbles demonstrate their extreme volatility and dynamic nature (Bordo and Levin, 2017). Policymakers and academics consider CBDCs as a form of controlled credit-based digital money: a "stablecoin" issued by national governments (e.g., Cunha et al., 2021; Wang et al., 2022). By launching CBDCs, central banks can maintain sovereign control over the stock of money in the economy while benefiting from digital technologies. Sissoko (2020) argues that introducing such central bank-backed digital currencies can balance the banking industry, while Buckley et al. (2021) and McLaughlin (2021) claim that CBDCs improve financial stability. Similarly, Tong and Jiayou (2021) employ a dynamic stochastic general equilibrium (DSGE) model to examine the economic impact of launching CBDCs. They find that CBDCs could mitigate systemic financial risk while the general public could hold them without liquidity or credit risk. Moreover, Lee et al. (2021a) address the main items of the CBDC design to balance benefits and risks using the two-tier or multi-tier ledger design.

As an emerging research area within the virtual currency sphere, the literature on CBDCs remains limited. Nevertheless, it can be classified into five main categories: The first category addresses the main concept of CBDCs (Yao, 2018); the characteristics and categories of CBDCs (Cunha et al., 2021); the implications of CBDCs (Li and Huang, 2021; Keister and Sanches, 2023); and the possible benefits and risks of monetary authorities' adopting CBDCs (Allen et al., 2022). The Federal Reserve (2022) defines a CBDC as "a digital liability of a central bank that is widely available to the general public". Bindseil (2019) states that CBDCs could be considered a third form of base money besides banknotes and overnight deposits. There are two types of CBDCs, namely wholesale and retail. The former, an account-based or token-based currency, is available to households and businesses. The latter is a restricted-access digital coin for interbank payments and securities settlements (Barontini and Holden, 2019). Retail CBDCs "universally accessible to all households" offer new options to the public for making payments and storing value. In addition, Bech and Garratt (2017) discuss the potential risk of introducing retail CBDC; for instance, if individuals could transfer their funds from commercial banks to risk-free central bank liabilities, the likelihood of a bank run is high. On the other hand, wholesale CBCDs are only available for financial institutions to clear transactions of digital tokenized financial assets (Bech et al., 2020).

The second category concerns the theoretical and technological aspects of designing CBDCs since launching such currencies

[4] This survey includes 81 central banks that represent emerging markets and advanced economies. For more detailed information about this survey, see Kosse and Mattei (2022).

requires architectural and technological design attention. For example, Lee et al. (2021b) develop a settlement system based on blockchain technology to manage CBDC settlement risks, while Sun et al. (2017) introduce a multi-blockchain data center model. This model would be a useful tool for central banks to manage the issuance of CBDCs and avoid double-spending issues.

The third category of studies addresses security and privacy. These critical challenges can significantly impact the legitimacy of CBDCs and people's confidence in them. According to the Bank for International Settlements (BIS), "while there were potential benefits to be made, the adoption of digital currencies outside the current financial system could reduce competition and create data privacy issues" (Inman and Monaghan, 2019; Borgonovo et al., 2021) argue that customers and investors would only accept CBDCs as a social payment medium if high levels of security and confidentiality are provided. In addition, Jabbar et al. (2023), utilizing a quantitative approach (survey), investigate whether customers would be willing to disclose private information for CBDC use. According to their findings, the majority of customers are concerned about disclosing personal information. However, these customers are willing to overlook these concerns if CBDC use provides substantial benefits. Finally, Yao (2018) argues that CBDCs should be developed as cryptocurrencies to increase their security and credibility.

The fourth category examines how CBDCs could affect the banking system and central banks. Chiu et al. (2019) use a general equilibrium model to investigate the impact of CBDCs on the intermediation of commercial banks. They confirm that CBDCs increase competition, expand intermediation, and positively impact loans, deposits, and output. However, Mancini-Griffoli et al. (2018) argue that CBDCs increase the cost of loan demands as banks are forced to increase deposit interest rates. Andolfatto (2021) demonstrates that CBDCs may induce commercial banks to increase their deposit rates, thereby increasing bank deposits, financial inclusion, and the digital economy (Andolfatto, 2021; Ozili, 2022). On the other hand, Selgin (2021) argues that the introduction of CBDCs by the central bank, specifically retail deposits, may result in financial instability. Similarly, Bindseil (2019) suggests that retail CBDCs may increase the instability of commercial bank deposit funding. This could be caused by a large-scale shift of commercial deposits into central bank deposit accounts during times of financial turmoil. However, the US Federal Reserve declares that these issues may be mitigated by optimal design for CBDCs (Federal Reserve, 2022). Zams et al. (2020) reveal that a "cash-like CBDCs model" would be best for Indonesia because it would increase financial inclusion and decrease shadow banking.Several studies have considered the new role of central banks (Yamaoka, 2022; Fernández-Villaverde et al., 2021; Williamson, 2021; Sinelnikova-Muryleva, 2020). For instance, Yamaoka (2022) summarizes the main challenges facing central bank digital currencies. In particular, CBDCs could cause a shift of funds from bank deposits to CBDCs, which might damage commercial banks. Sinelnikova-Muryleva (2020) argued that monetary authorities could develop monopolist power over deposits, which might cause a bank run. Due to the absence of limits on individual holdings, deposits held by individuals are expected to be subject to high volatility. This could have an impact on the bank's profitability and lending activities. Furthermore, CBDC could be regarded as a safe haven during times of financial crisis. This may make deposits in the banking system unstable, increasing the likelihood of bank panic (BIS, 2021).

The fifth category investigates the positive and negative effects of CBDCs on the current monetary system. According to Bordo and Levin (2017), for example, central bank digital currencies could mitigate the problems of the zero lower bound and the liquidity trap by reducing the nominal value of CBDCs, which would allow deeply negative interest rates. This would increase the efficiency of monetary policy during deflationary and deep recessionary phases (Bordo and Levin, 2017; Cunha et al., 2021). Yamaoka (2022) takes the debate one step further by suggesting that, during the era of CBCDs, banking regulation, supervision, and the monetary system should be reviewed. Finally, Davoodalhosseini (2021) examines the optimal monetary policy if agents can choose between cash and a CBDC. The findings showed that when the cost of holding CBCDs is low, the optimal monetary policy only depends on CBCDs, whereas only cash is used when this cost is high. Further, Ozili (2021) states that monetary authorities could leverage on their monetary powers and the citizens' trust in government-backed money. However, Elsayed and Nasir (2022) argue that CBDCs could bring new challenges to monetary policy with regard to achieving price stability. Fegatelli (2022) examines the conditions under which the European Central Bank (ECB) could introduce CBDC without causing a credit crisis or bank disintermediation in the euro area. The author concluded that CBDC could be used as an additional tool for withdrawing large amounts of idle or excess reserves without affecting bank profitability or competitiveness.

Given the above background, our study aims to contribute to the literature in two main respects. First, although CBDCs will shortly be launched worldwide, only a limited number of empirical studies have analyzed their potential effects on the financial markets with the exception of recent publications by Wang et al. (2022, 2023) and Scharnowski (2022). Second, in contrast to previous empirical studies, this paper aims to make the first attempt to investigate the response of cryptocurrency markets and stock markets to CBDC news by utilizing a time-varying parameter vector auto-regression (TVP-VAR) model with stochastic volatility.

3. Data description and preliminary analysis

To investigate the impact of CBDCs on the financial and cryptocurrency markets, we collected weekly data from January 2015 to December 2021. The starting date for the analysis is determined by the availability of the CBDC news indices computed by Wang et al. (2022), originally available at a weekly frequency.[5] We prefer using weekly data to increase the number of observations. In addition, the time-varying structure of the variance-covariance matrix of the TVP-VAR model also enables us to capture the volatile behavior of the high-frequency financial variables (Primiceri, 2005; Koop et al., 2009).

Except for the CBDC news indices, all data, namely S&P 500 index, CBOE Volatility Index (VIX), cryptocurrency policy uncertainty

[5] The CBDCs new indices are available for download at https://sites.google.com/view/cryptocurrency-indices/the-indices/cbdc-indices?authuser= 0.

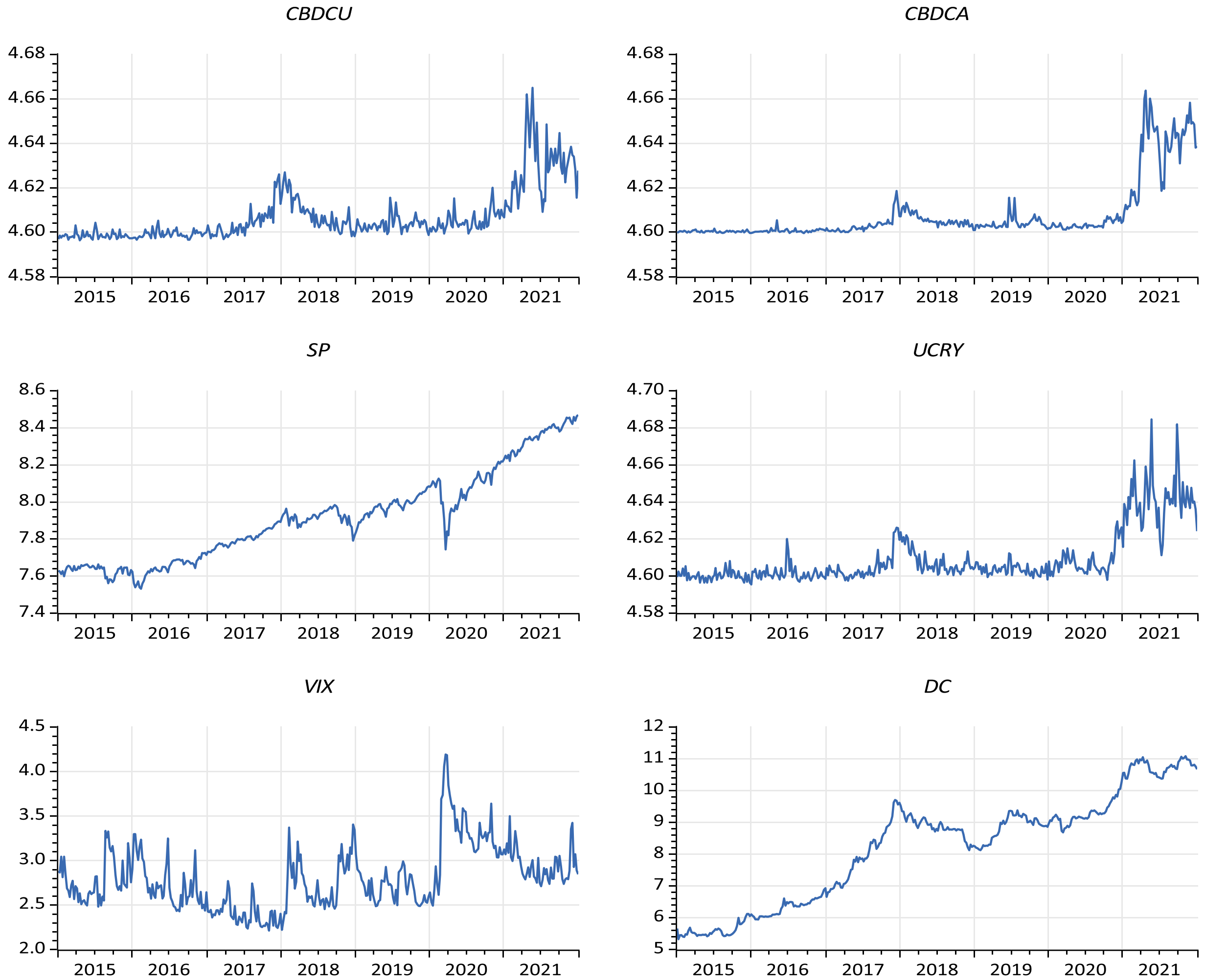


Fig. 1. Dataset.

index (UCRY), and Bitcoin price (DC), are retrieved from the Refinitiv Eikon DataStream database (Refinitiv Eikon Datastream, 2022). Hence in the estimation of the TVP-VAR model, the following vector of the endogenous variables is considered:[6].

$$y_t' = [CBDC_t\ VIX_t\ SP_t\ UCRY_t\ DC_t] \tag{1}$$

where $CBDC_t$ denotes the natural log of the CBDC News Uncertainty index $(CBDCU_t)$ calculated by Wang et al. (2022);[7] SP_t is the natural log of the S&P 500 index representing the performance of 500 firms domiciled in the US, including approximately around eighty percent of the total US stock market value; VIX_t is the natural log of the CBOE Volatility Index, computed from the prices of the options premium in the S&P 500 index; $UCRY_t$ is the natural log of the cryptocurrency policy uncertainty index; DC_t is the natural log of the Bitcoin price, which proxies for the cryptocurrency markets with the highest market capitalization. Fig. 1 presents the variables in their natural log form.

A battery of unit root tests is conducted to examine the time-series properties of these variables. The linear unit root test results, i.e., Augmented Dickey and Fuller (1981) and Phillips and Perron (1988), are inconclusive regarding the variables' integration properties.[8] Therefore, Lee and Strazicich (2003) unit root test, which allows for two endogenous structural breaks, is also implemented to

[6] Similar to Wang et al. (2002), this article employs Cholesky decomposition based on the recursive ordering of the variables from the most exogenous to the most endogenous in the estimation of the VAR. In this setup, the CBDC news uncertainty index and Bitcoin returns are ordered first and last, respectively, as we are investigating the effects of CBDC news on the cryptocurrency market.

[7] Another CBDC news index is the Central Bank Digital Currency Attention Index (CBDCA). We use CBDC uncertainty as they follow the same trend over the analysis period with a high positive correlation with a coefficient of 91.59% (see Table A1). Figure A1, which compares the linear responses obtained from VAR estimates using those indices shows that the variables respond to both indices in qualitatively the same direction.

[8] These test results of those test are not reported but are available upon request from the corresponding author.

Table 1
Descriptive statistics of the variables.

	CBDCU	*CBDCA*	*VIX*	*SP*	*UCRY*	*DC*
Mean	4.606	4.607	7.914	4.609	2.797	8.228
Median	4.603	4.602	7.906	4.603	2.740	8.773
Maximum	4.664	4.663	8.469	4.684	4.190	11.080
Minimum	4.596	4.599	7.530	4.595	2.212	5.327
Std. Dev.	0.011	0.013	0.244	0.014	0.346	1.699
Skewness	2.119	2.449	0.544	2.088	0.933	-0.216
Kurtosis	7.798	7.863	2.420	7.321	4.185	1.910
Jarque-Bera	625.182	726.825	23.183	551.029	74.575	20.955
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Sum	1686.121	1686.421	2896.817	1687.056	1023.852	3011.488
Sum Sq. Dev.	0.049	0.067	21.823	0.081	43.912	1054.445
Observations	366	366	366	366	366	366

Notes: CBDCU, CBDCA, VIX, SP, UCRY, and DC denote the Central Bank Digital Currency Uncertainty Index, Central Bank Digital Currency Attention Index, CBOE Volatility Index, S&P 500 index, cryptocurrency policy uncertainty index, and Bitcoin price, respectively. The Jarque-Bera test is employed as a test for normality.

Table 2
Break Unit Root Tests.

Series	Break Model		Crash Model	
$CBDCU_t$	-4.967 *		-3.598 * *	
	(−5.7923, −5.2250, −4.9509)		(−4.1951, −3.6252, −3.3109)	
	2018:03:09	2021:03:26	2017:07:07	2021:04:16
SP_t	-5.309 * *		-3.683 * *	
	(−5.7077, −5.1476, −4.8970)		(−4.1951, −3.6252, −3.3109)	
	2016:11:25	2020:04:17	2016:01:29	2020:10:30
ΔSP_t	-20.618 * **		-20.845 * **	
	(−5.7145, −5.1310, −4.8450)		(−4.1957, −3.6254, −3.3107)	
	2016:02:05	2018:05:18	2018:02:02	2020:01:24
VIX_t	-7.391 * **		-7.142 * **	
	(−5.7077, −5.1476, −4.8970)		(−4.1951, −3.6252, −3.3109)	
	2016:12:02	2020:02:21	2018:02:02	2020:02:21
$UCRY_t$	-7.163 * **		-3.987 * *	
	(−5.7923, −5.2250, −4.9509)		(−4.1951, −3.6252, −3.3109)	
	2017:10:27	2020:11:13	2020:03:27	2021:02:05
DC_t	-4.174		-2.545	
	(−5.7169, −5.1987, −4.9626)		(−4.1951, −3.6252, −3.3109)	
	2017:09:01	2020:03:13	2016:06:03	2017:05:12
ΔDC_t	-17.308 * **		-3.657 * *	
	(−5.6975, −5.0858, −4.8144)		(−4.1957, −3.6254, −3.3107)	
	2017:09:08	2018:11:30	2018:02:23	2019:08:30

Note: * , * *, and * ** show statistical significance for 10, 5, and 1%, respectively, for both the break and crash models. Values in parentheses represent the critical value at 1, 5, and 10% significance levels, respectively.

determine the impact of local and global important events (e.g., the COVID-19 pandemic) on the degree of integration of the time series. The Lee and Strazicich (2003) test results, presented in Table 2, indicate that SP_t and DC_t can be treated as $I(1)$, whereas the remaining variables were stationary at their level. Therefore, the log first difference form of the variables is employed in the estimation of the TVP-VAR model.

A wide range of descriptive statistics of the variables is summarized in Table 1. The means of the weekly central bank digital currency, CBOE Volatility Index, S&P 500, cryptocurrency policy uncertainty indexes, and Bitcoin price are all positive. Bitcoin price has the highest mean value, which emphasizes that its high price increases over our sample period, followed by the VIX index. The cryptocurrency policy uncertainty index and Bitcoin price are more volatile than the S&P 500. The Jarque-Bera test statistics for normality imply a rejection of the null hypothesis of normality at all significance levels. Furthermore, it is observed that the majority of the variables exhibit excess skewness and kurtosis.[9]

4. The model

The VAR approach is most frequently used in the literature to investigate indices' impact on financial assets. This model can also determine the effects of CBDC indices on the financial and cryptocurrency markets and their variations (Lucey et al., 2022). The linear version of the VAR model can be represented as in Eq. 2:

[9] In addition, the Pearson correlations between the variables are presented in Table A1. The CBDCU index has a strong positive correlation with the UCRY index, but only a moderate correlation with the VIX index. Additionally, it has a positive correlation with the SP index and Bitcoin prices.

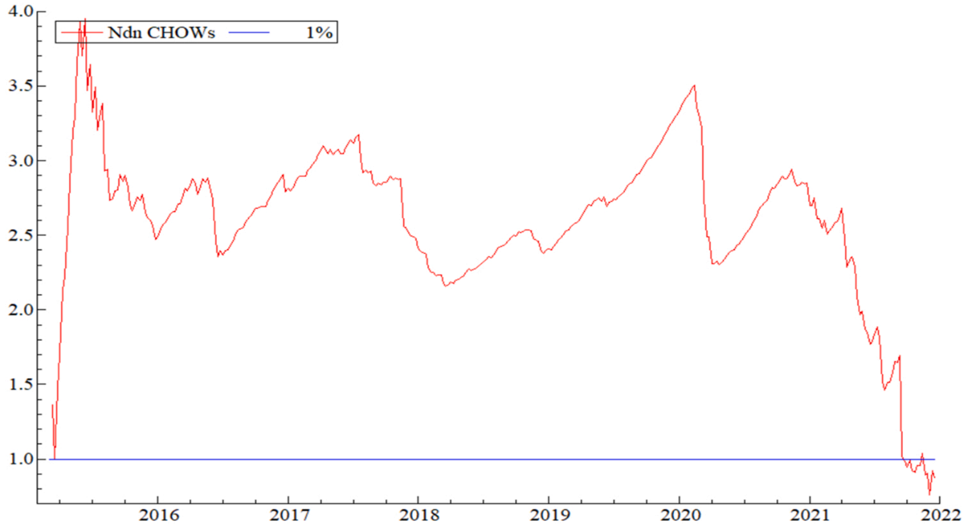


Fig. 2. Chow breakpoint test.

$$y_t = c + B_1 y_{t-1} + \ldots + B_p y_{t-p} + \varepsilon_t \tag{2}$$

Following Primiceri (2005), a Bayesian VAR model with time-varying parameters and stochastic volatility consists of sets of state-space equations. Accordingly, the measurement equation of the TVP-VAR model can be represented by

$$y_t = c_t + B_{1,t} y_{t-1} + \ldots + B_{p,t} y_{t-p} + \varepsilon_t = X_t \Theta_t + \varepsilon_t, \tag{3}$$

where c_t and $B_{1,t..p,t}$ are the time-varying intercept parameters and vectors of the time-varying coefficients, respectively. The matrix of endogenous variables, including an intercept term, is denoted by the X_t. The disturbance terms which are shown with ε_t are assumed to have equal variance and follow a normal distribution with a zero mean and a time-varying covariance matrix Ω_t. The variance-covariance matrix of residuals denoted by Ω_t is decomposed to calculate the dynamic interactions among the variables as follows:

$$\Omega_t = A_t^{-1} H_t (A_t^{-1})' \tag{4}$$

$$A_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 & 0 \\ \alpha_{51,t} & \alpha_{52,t} & \alpha_{53,t} & \alpha_{54,t} & 1 \end{bmatrix} \quad H_t = \begin{bmatrix} h_{1,t} & 0 & 0 & 0 & 0 \\ 0 & h_{2,t} & 0 & 0 & 0 \\ 0 & 0 & h_{3,t} & 0 & 0 \\ 0 & 0 & 0 & h_{4,t} & 0 \\ 0 & 0 & 0 & 0 & h_{5,t} \end{bmatrix} \tag{5}$$

where $A_t$is the lower triangular matrix externalizes the contemporaneous relationships and H_t is a matrix containing the stochastic volatilities on the diagonals.

Finally, the parameters vary with the following state equations, which are shown below:

$$\begin{array}{r} \Theta_t = \Theta_{t-1} + v_t \\ \alpha_t = \alpha_{t-1} + \zeta_t \\ \ln h_{i,t} = \ln h_{i,t-1} + \eta_t \end{array} \quad \begin{bmatrix} u_t \\ v_t \\ \zeta_t \\ \eta_t \end{bmatrix} \sim N\left[0, \begin{bmatrix} \Omega_t & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & Z \end{bmatrix}\right] \tag{6}$$

The time-varying parameters Θ_t and α_t are assumed to pursue a random walk without a drift process and distribute the normal distribution, as denoted by the first two equations in (5).[10] Based on the existing financial literature, the vector of the stochastic volatilities, h_t, is assumed to follow a geometric random walk. Furthermore, the disturbances of the measurement equation and the three transition equations are supposed to be independent, as pointed out by Primiceri (2005), to simplify the inference and increase the efficiency of the estimation algorithm.

5. Empirical results

A prerequisite to estimating time-varying parameter models, the parameter stability of the VAR model is examined with the VAR

[10] Since the random walk model is not stationary, the stability constraint is imposed on the evolution of the time-varying parameters, following Cogley and Sargent (2005).

Table 3
Convergence Diagnostics.

Parameter	Mean	Std. Dev.	95%L	95%U	Geweke	Inef. Factor
$(\Sigma_{\Theta})_1$	0.019	0.021	0.016	0.024	0.642	17.260
$(\Sigma_{\Theta})_2$	0.018	0.001	0.015	0.022	0.516	16.580
$(\Sigma_{\alpha})_1$	0.054	0.013	0.035	0.085	0.689	80.980
$(\Sigma_{\alpha})_2$	0.056	0.097	0.023	0.238	0.339	27.120
$(\Sigma_{h})_1$	0.466	0.077	0.332	0.631	0.155	54.700
$(\Sigma_{h})_2$	0.644	0.098	0.466	0.849	0.138	55.500

Notes: In this table, the estimated values of the selected parameters in the measurement, simultaneous shocks and stochastic volatilities equations are denoted by Σ_{Θ}, Σ_{α} and Σ_{h} respectively, as defined in Eq. (6).

Chow breakpoint test based on recursive least squares. Fig. 2 presents the Chow breakpoint test results. The recursive breakpoint test indicates the presence of a significant number of parameter instabilities in the linear model, which can be attributed to the effects of the fluctuations in the financial markets during the analysis period. The recursive Chow breakpoint test results further demonstrate that the COVID-19 pandemic coincided with the end of the analysis period, resulting in severe parameter instability. This implies that a time-varying model might be able to better account for nonlinearity in the residual generating mechanism.

Having detected instabilities in the linear model, the TVP-VAR model is estimated using the Markov Chain Monte Carlo (MCMC) technique with the Bayesian approach. As Nakajima et al. (2011) suggested, the multi-move sampler of Watanabe and Omori (2004) is used to generate samples from the exact posterior density of the stochastic volatility.[11] In contrast to other sampling methods, such as the Metropolis-within-Gibbs sampler that was utilized by Primiceri (2005), the Multi-move sampler does not require the reservation of a specific number of initial observations to initialize starting values of the parameters. As a result, we are able to estimate the TVP-VAR without experiencing any loss in the estimation sample. We use this multi-move sampler to extract 50,000 samples from the posterior distribution, discarding the first 5000 as a burn-in sample.

Table 3 displays the standard deviations, lower- and upper-95% confidence intervals, and posterior averages of the chosen parameters based on the MCMC estimation of the TVP-VAR model. In addition, convergence diagnostics (CD) and inefficiency statistics are also conducted (see Table 3). Based on Geweke (1992) statistics, the null hypothesis of convergence to the posterior distribution is not rejected for the parameters at 5 level of significance. Furthermore, the inefficiency factors are less than one hundred, indicating that the number of iterations is sufficient for a stable estimation of the TVP-VAR model.[12]

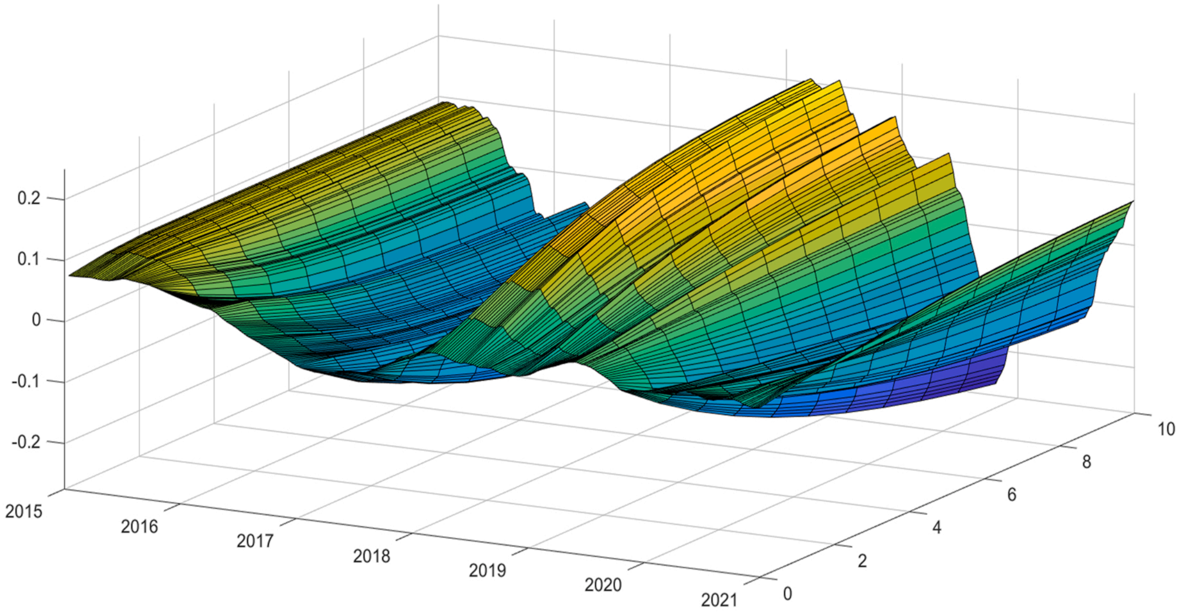
After the estimation, we examine the effects of the CBDCU shocks on the stock returns, VIX, cryptocurrency policy uncertainty index, and cryptocurrency returns. Figs. 3–6 illustrate the time-varying responses to CBDCU shocks. In panel (a) of each figure, the responses are plotted in a three-dimensional space for the horizons $t = 0, 1, 2, \ldots, 10$. Panel (b) of each figure shows the cumulative responses at the horizon $h = 10$plotted with their two standard error confidence bands to evaluate the significance of the shocks over the sample period.[13]

Fig. 3 reports the time-varying responses of VIX to CBDCU shocks. The results from the linear VAR indicate that CBDCU shocks have positive but insignificant effects on VIX (see Fig. A2). On the other hand, the time-varying responses indicate that the effects of CBDCU shocks vary in terms of significance and sign over time. For instance, CBDCU shocks initially have positive but insignificant effects on the VIX, but statistically significant negative effects between January 2017 and August 2017, then significant positive effects between January 2018 and June 2019. CBDCU shocks have the largest adverse effects on VIX in October 2019, which can be linked to the emergence of some CBDC news. For instance, at that time, the Central Bank of the Republic of China published its most recent plans for cryptocurrency with government approval. Similarly, the Central Bank of the Russian Federation investigated the feasibility of establishing a CBDC, while Banque Internationale Luxembourg and Seba Bank successfully tested CBDCs for securities transmission. The Turkish Central Bank also initiated CBDC plans, and the Thai central bank developed its own CBDC. Meanwhile, Beijing permitted CBDC withdrawals from more than 3000 ATMs. After 2019 the responses decline and become insignificant till the end of the investigation period. Thus, the general results indicate that CBDCU shocks can significantly increase or decrease VIX volatility depending on the period. However, linear VAR estimates of Wang et al. (2022) indicated that CBDCU shocks significantly increase the volatilities of VIX. Additionally, Minesso et al. (2022) demonstrate that introducing CBDC can considerably boost the shocks' global spillovers and

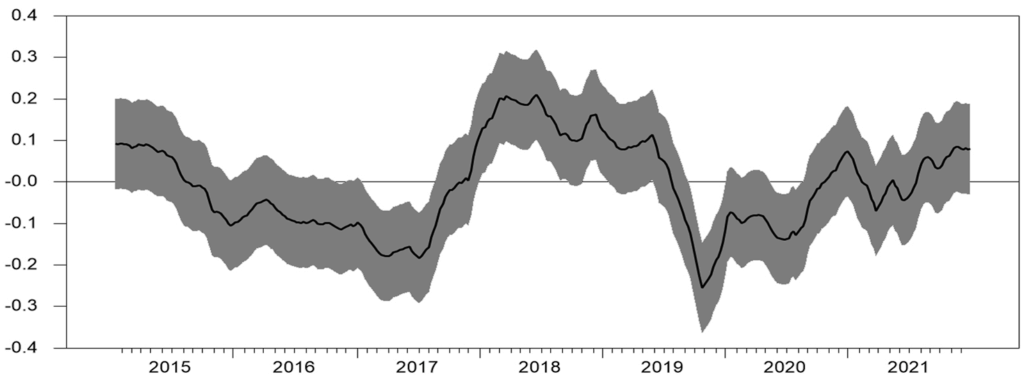
[11] The number of lags in the VAR are selected using the Akaike Information Criterion (AIC). The following priors in Nakajima (2011) are used for the calibration of the TVP-VAR model: $\Sigma_{\beta} \sim IW(25, 0.01I)$, $(\Sigma_{\alpha})_i^{-2} \sim G(5, 0.02)$, $(\Sigma_h)_i^{-2} \sim G(5, 0.02)$. $(\Sigma_{\alpha})_i^{-2}$ and $(\Sigma_h)_i^{-2}$ shows the i^{th} diagonal elements of the Σ_{α} and Σ_h matrices, respectively. For the MCMC algorithm flat priors were used $\mu_{\beta_0} = \mu_{a_0} = \mu_{h_0}$ and $\Sigma_{\beta_0} = \Sigma_{a_0} = \Sigma_{h_0}$. Detailed information about the estimation steps for the TVP-VAR model are available in Nakajima (2011).

[12] The CD test is utilized to evaluate the convergence of the Markov chain by comparing the first and last draws. If MCMC sampling yields stable estimates, the posterior distribution of the parameters should converge to standard normal; consequently, the null hypothesis of posterior distribution convergence cannot be rejected. Figure A1 of the TVP-VAR model presents additional diagnostic tests in addition to the CD test. The findings reinforce the convergence of the posterior distribution. First, the sample paths of the parameters exhibit stable behavior, as the autocorrelation functions of their standard errors, as shown in the top row of Figure A1, quickly decay to zero. Second, the final row of Figure A1 indicates that the posterior distribution of the estimated parameters closely resembles the Gaussian distribution.

[13] Following Nakajima (2011), time-varying responses are generated by equating the initial shock size to the time-series average of stochastic volatility over the investigation period.



(a) Time-varying cumulative responses



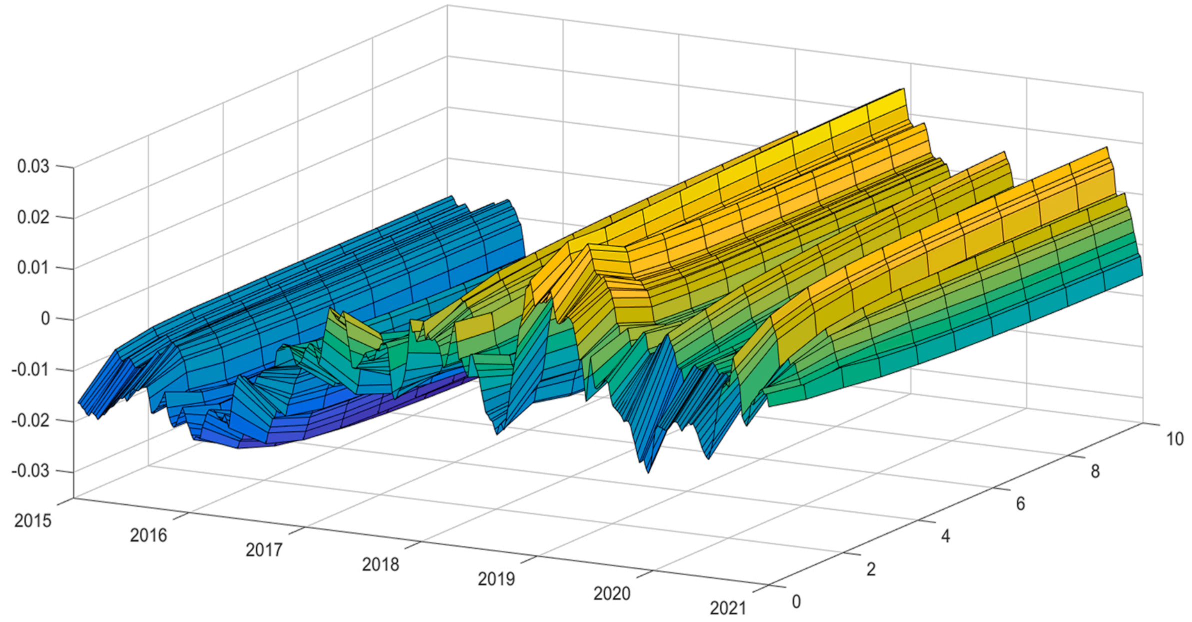
(b) Time-varying responses at $h = 10$ with ±2 standard error bands

Fig. 3. Responses of VIX to CBDC news Uncertainty Index.

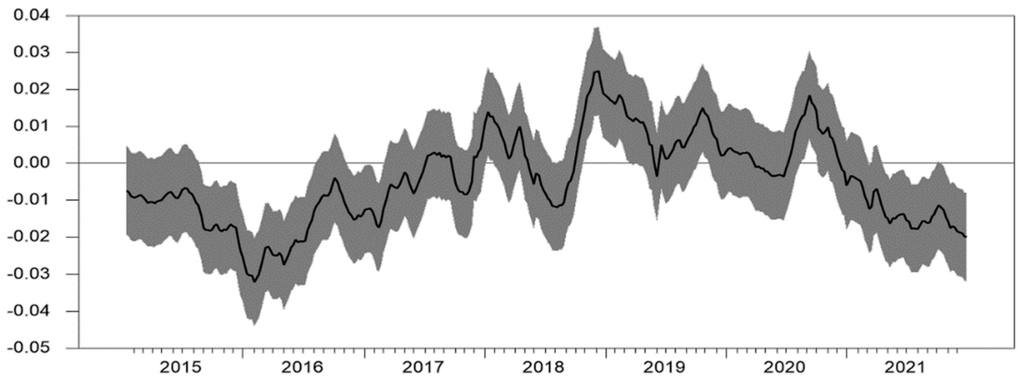
strengthen international linkages. It is also noted that the size of these impacts depends on the specific design of CBDC.

Fig. 4 shows the time-varying responses of the S&P 500 returns to the CBDC shocks. The linear responses reveal that CBDCU shocks had a significant positive impact on SP stock returns. In contrast, the time-varying responses demonstrate that the magnitude and sign of the shock's impact fluctuates over time.[14] More specifically, CBDCU shocks initially have adverse effects on the S&P 500, with significant negative effects between August 2015 and August 2016, including the largest negative effect in February 2016. During this period, Ben Brodent Deputy Governor of the Bank of England gave a speech about the economic impacts of CBDCs. In addition, falling oil prices at that time reduced market confidence, which seems to have caused a severe decline in the S&P 500 index. On the other hand, CBDCU shocks have significant positive effects between December 2017 and January 2018, while the most positive significant effects are recorded between October 2018 and March 2019. While responses remain significant and positive from August 2020 to November 2020, CBDC news shocks have a negative impact on the S&P 500 from March 2021 until the end of the analysis period due

[14] See Figure A2 for the responses obtained from the linear VAR model.



(a) Time-varying cumulative responses



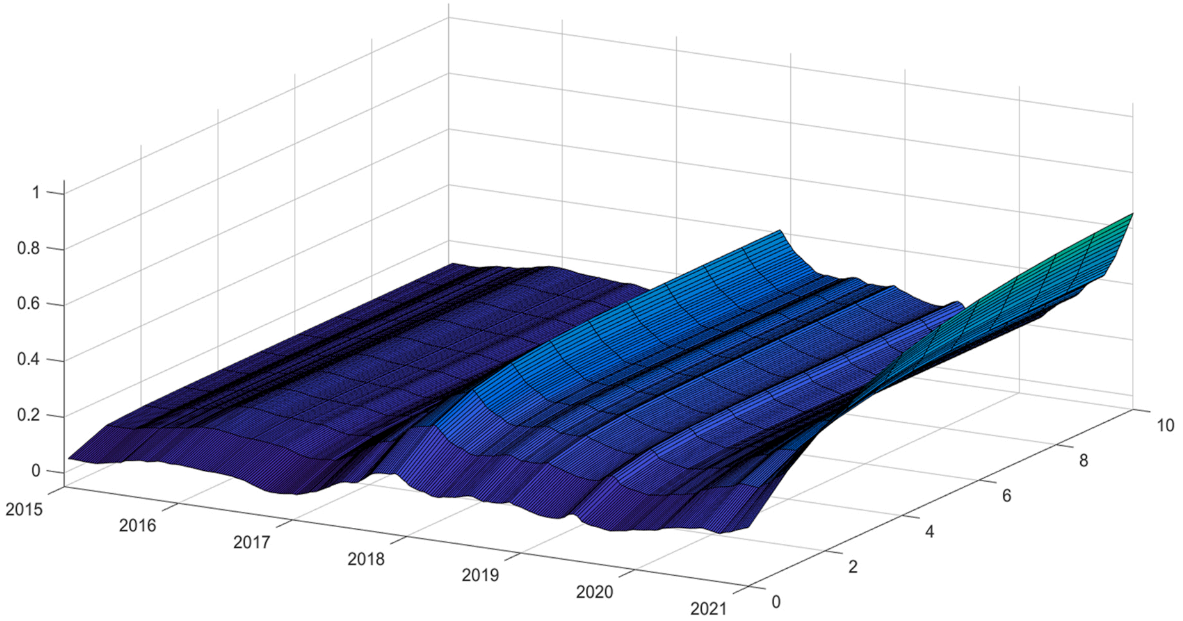
(b) Time-varying responses at $h = 10$ with ±2 standard error bands

Fig. 4. Responses of S&P 500 to CBDC news Uncertainty Index.

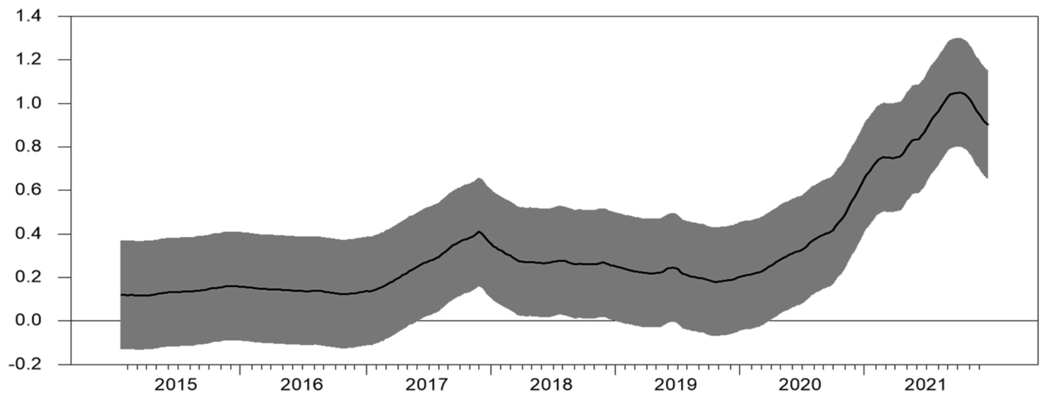
to lockdown measures implemented during the COVID-19 pandemic. The evidence on the time-varying effects of CBDC news on stock returns is aligned with Li et al. (2022), where the TVP-VAR model is employed to investigate the reaction of the fintech sector to CBDC signals. In that study, the fintech sector's positive response to CBDC signals is revealed, but this response gradually declines over time. It is further concluded that the participation of fintech firms in the People's Bank of China (PBOC) CBDC project drew investors' attention to the fintech industry in the capital market.

Fig. 5 shows the response of the cryptocurrency policy uncertainty index (UCRY) to CBDC news. The linear responses indicate that CBDC news shocks has a significantly impact on UCRY (see Fig. A2). In contrast with the other responses, the time-varying responses of UCRY to CDBCU shocks are positive and stable throughout the period. The first significant positive response to shocks is recorded in July 2017 and January 2019. After that time, the earlier insignificant responses during the pandemic increase significantly, while UCRY's responses have reached their peak in early October 2021, when the Bitcoin price surpassed 60.000 US dollars. This finding is consistent with the findings of Wang et al. (2022), who discovered that CBDCU shocks have a positive and significant effect on UCRY.

The response of Bitcoin returns (DC) to CBDCU shocks is illustrated in Fig. 6. The linear responses indicate that CBDCU shocks have a negative but insignificant effect on Bitcoin returns (see Fig. A1). For the time-varying responses, there were significant positive responses early on, in October 2015 and December 2015, when China made the application of the Anti-Money Laundering Law to digital currencies stricter. As already mentioned, Ecuador launched the world's first state-run electronic payment system at that time. The responses of DC to CBDCU shocks then become negative, with significant responses, particularly in early 2017. The largest adverse reactions to CBDCU shocks are observed between January 2018 and January 2019, with the largest negative responses in June 2019. During this time, China, Russia,



(a) Time-varying cumulative responses



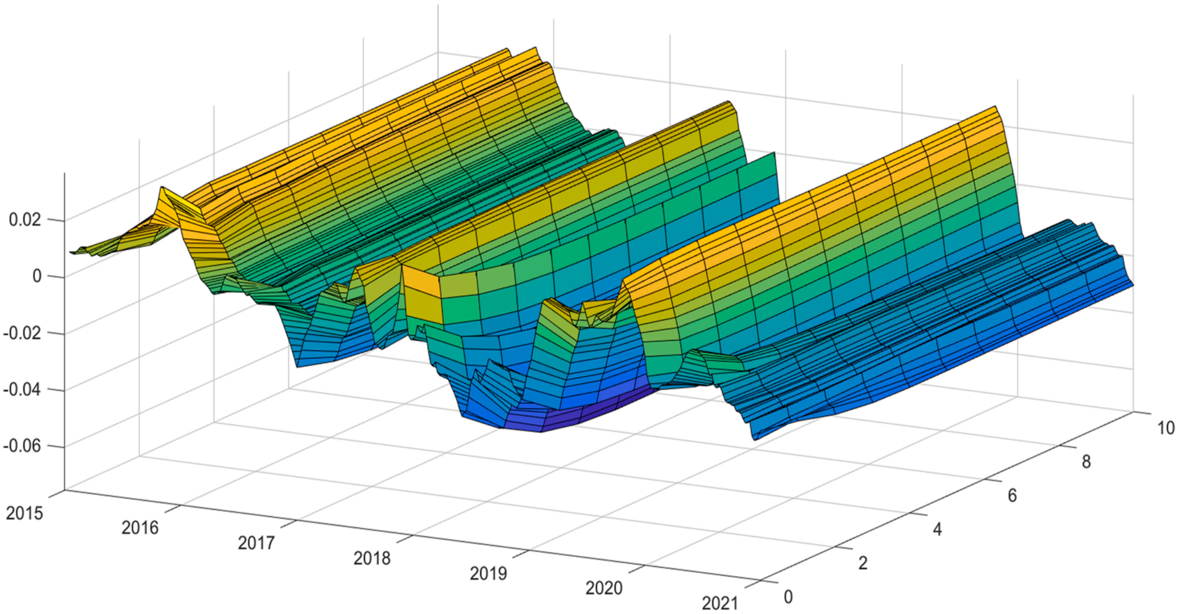
(b) Time-varying responses at $h = 10$ with ±2 standard error bands

Fig. 5. Responses of cryptocurrency policy uncertainty to CBDC news Uncertainty Index.

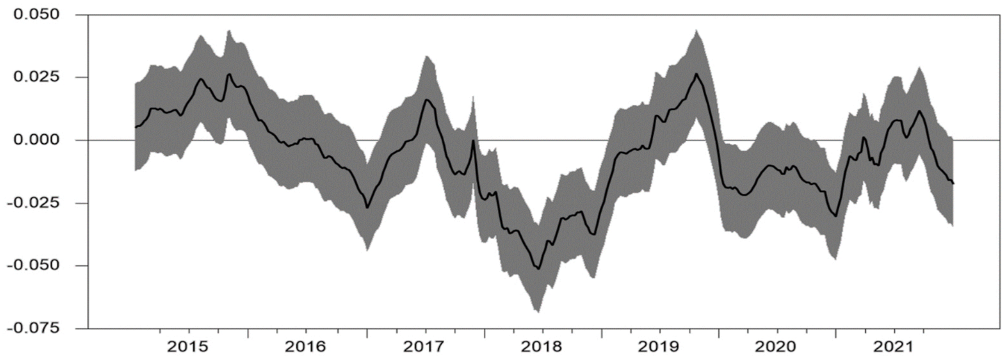
Turkey, and Luxembourg introduced CBDC regulations, as described previously. CBDCU shocks also have a significant negative effect in January 2021, when Bitcoin's value fell by over 20%. The responses of DC to CBDCU shocks then become insignificant towards the end of the analysis period. These results contradict those of Wang et al. (2022), whose estimation of a linear structural vector autoregressive (SVAR) model demonstrated that CBDCU shocks can substantially increase Bitcoin's short-term volatility.

Along with time-varying impulse responses, we also conduct the time-varying variance decomposition analysis to uncover the contribution of CBDCU shocks on the UCRY and Bitcoin return shocks over a 10-week forecast horizon. The results, in general, corroborate our findings from the time-varying responses. Table 4 and Fig. 7 present the forecast error variance decomposition analysis from the linear VAR and TVP-VAR models, respectively. The linear forecast error decomposition results imply that CBDCU shocks have accounted for a considerable portion of the UCRY shocks. For example, at the $h = 10$ horizon, CBDCU explains 59.13% of the variation in the UCRY shocks, which is more than the UCRY shock itself (39.66%). VIX and SP, however, have very limited explanatory power at 1.13% and 0.04%, respectively. In contrast, most of the variation in the Bitcoin return shocks (DC) is explained by the own shock of the variable. For instance, at $h = 10$, CBDCU and UCRY shocks explain only around one percent of the variation in DC shocks, while the explanatory power of VIX and S&P 500 is even less than one percent. The own shock of DC explains around 97.22% of the variation.

Fig. 7 shows the time-varying forecast error decompositions obtained from the TVP-VAR model estimation at $h = 10$ day horizon. The results were remarkably different from their linear counterparts. In the time-varying case, most of the variation in the UCRY was



(a) Time-varying cumulative responses



(b) Time-varying responses at $h = 10$ with ±2 standard error bands

Fig. 6. Responses of Bitcoin Prices to CBDC news Uncertainty Index.

explained by its own shocks at the beginning of the investigation period (76.66% on 1/16/2015). In comparison, S&P 500 returns can explain 20.42%. At that time, CBDCU shocks only explained 2.83% of the variation in the UCRY. The explanatory power of VIX was obtained as less than one percent at that time. The explanatory power of CBDCU then increases so that CBDCU shocks become the largest contributor by the last week of May 2017, accounting for more than half of the variation in UCRY shocks (with 0.516888 as of 5/26/2017). CBDCU has the greatest explanatory power in the first week of December 2017 at 83.58%, while the own shock of UCRY explains 14.17% of the variation. It is worth mentioning that this period is associated with the important CBDC news. For instance, digital currency is sponsored by the US government and managed by the Federal Reserve. At the same time, the Central Bank of China tested a digital currency, and the Bank of England, Bank of Canada, European Central Bank, Bank of Russia, Bank of Japan, and Bank of Australia were studying the possible introduction of CBDC. After falling below 30% until April 2018, the explanatory power of CBDCU increase to over 60% again by November 2018 (on the last week of November 2018, 65.43%, with 30.57% explained by its own shock). In June 2019, it reaches a new high of 68.75%. CBDCU shocks thus become the most important determinant of UCRY shocks during the COVID-19 pandemic, with the second-highest peak of 78.89% in April 2021. Bitcoin reaches its historical peak at this time while the Bank of England and the Treasury set up a new task force to analyze the objectives of determining a CBDC. At that time, Wall Street banks were getting used to the idea that CBDCs would be the next financial disruptor. Some scholars were worried about the convertibility of the Renminbi (RMB). After falling below 30% until April 2018, the explanatory power of CBDCU increased above 60% again in 2018. In the same period, 30.57% of the changes in the variable were explained by its own shock. The explanatory power of

Table 4
Linear forecast error decompositions.

Variance Decomposition of *UCRY*						
Period	SE.	*CBDCU*	*VIX*	*SP*	*UCRY*	*DC*
1	0.444	36.349	0.157	0.170	63.323	0.000
2	0.583	43.361	0.166	0.100	56.345	0.025
3	0.674	48.320	0.292	0.076	51.287	0.023
4	0.741	51.725	0.430	0.064	47.756	0.023
5	0.793	54.099	0.567	0.057	45.250	0.023
6	0.834	55.789	0.698	0.053	43.434	0.024
7	0.866	57.016	0.819	0.050	42.088	0.025
8	0.893	57.924	0.932	0.048	41.067	0.026
9	0.914	58.608	1.035	0.047	40.279	0.028
10	0.932	59.131	1.131	0.046	39.661	0.029
Variance Decomposition of *DC*						
Period	**SE.**	*CBDCU*	*VIX*	*SP*	*UCRY*	*DC*
1	0.474	0.081	0.000	0.015	0.289	99.612
2	0.621	0.632	0.236	0.140	1.041	97.948
3	0.719	0.852	0.235	0.140	1.184	97.586
4	0.788	0.964	0.236	0.140	1.200	97.457
5	0.838	1.028	0.239	0.140	1.199	97.391
6	0.876	1.071	0.242	0.140	1.200	97.345
7	0.905	1.102	0.244	0.140	1.205	97.307
8	0.927	1.126	0.246	0.140	1.210	97.276
9	0.944	1.145	0.247	0.140	1.216	97.250
10	0.958	1.160	0.248	0.140	1.221	97.229

Table 5
Time-varying forecast error decompositions.

	Variance Decomposition of UCRY					Variance Decomposition of DC				
	CBDCU	*VIX*	*SP*	*UCRY*	*DC*	*CBDCU*	*VIX*	*SP*	*UCRY*	*DC*
2015S1	0.157	0.142	0.000	0.699	0.000	0.229	0.053	0.001	0.132	0.583
2015S2	0.030	0.194	0.000	0.775	0.000	0.120	0.440	0.002	0.092	0.344
2016S1	0.025	0.096	0.000	0.878	0.000	0.056	0.336	0.003	0.141	0.462
2016S2	0.081	0.100	0.000	0.817	0.000	0.060	0.287	0.001	0.140	0.510
2017S1	0.626	0.002	0.000	0.370	0.000	0.052	0.006	0.001	0.080	0.860
2017S2	0.755	0.032	0.000	0.211	0.000	0.163	0.053	0.000	0.094	0.689
2018S1	0.441	0.025	0.000	0.532	0.000	0.328	0.134	0.000	0.101	0.436
2018S2	0.526	0.060	0.001	0.412	0.000	0.153	0.133	0.004	0.069	0.639
2019S1	0.648	0.035	0.001	0.314	0.000	0.153	0.006	0.001	0.029	0.809
2019S2	0.140	0.047	0.001	0.810	0.000	0.006	0.017	0.008	0.118	0.849
2020S1	0.356	0.015	0.003	0.624	0.000	0.071	0.082	0.028	0.074	0.742
2020S2	0.267	0.013	0.000	0.719	0.000	0.501	0.196	0.003	0.077	0.221
2021S1	0.648	0.008	0.000	0.342	0.000	0.377	0.054	0.004	0.209	0.354
2021S2	0.463	0.023	0.000	0.513	0.000	0.336	0.258	0.002	0.100	0.301

Table 6
Descriptive properties of the time-varying responses.

	CBDCU − > SP	*CBDCU − > VIX*	*CBDCU − > UCRY*	*CBDCU − > DC*
Min.	-0.032	-0.363	0.117	-0.051
Max	0.025	0.101	1.050	0.026
Mean	-0.004	-0.118	0.325	-0.006
Std. Dev.	0.011	0.108	0.249	0.017

CBDCU again peaked at 68.75% in June 2019, making CBDCU shocks the most important determinant of UCRY shocks in the COVID-19 period, reaching the second-highest explanatory power level in April 2021, at 78.89%. At that time, the Bank of England and the Treasury joined together to investigate the objectives of establishing a CBDC named Bitcoin. At that time, Wall Street banks were getting used to the idea that CBDCs would be the next big financial disruptor.

The bottom of Fig. 7 presents the time-varying forecast error decomposition of Bitcoin returns (DC). The first thing to note is that the explanatory power of the variables in explaining DC shocks followed a more volatile trajectory than the time-varying variance decomposition of UCRY. On average, CBDCU shocks explain 15.38% of the changes in DC over the period. The explanatory contribution of CBDCU shocks is lower at the beginning of the analysis period before increasing over time. For example, in the first week of October 2015, CBDCU shocks account for 41.06% of the changes in DC, whereas SP and UCRY shocks explain 15.89% and 13.53%, respectively. DC's power to explain its own shocks is estimated at 29.37%. CBDCU shocks peak at 57.40% in the first week of December 2017. CBDCU shocks explain most of the variation between April 2018 and December 2018, after the own shock of the variable.

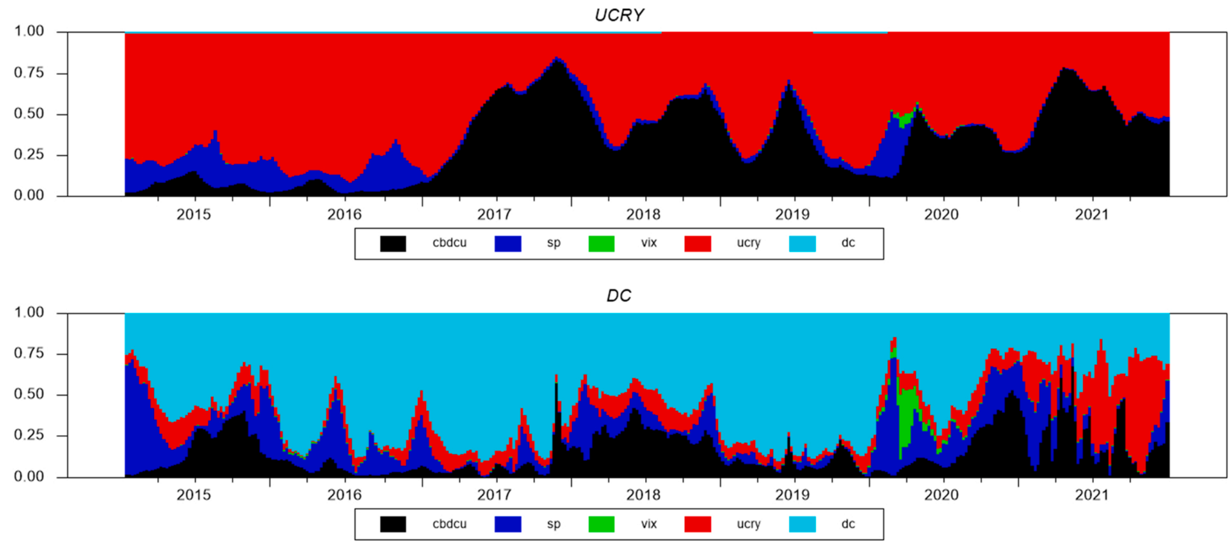


Fig. 7. Time-varying forecast error decompositions.

CBDCU shocks have reached their largest explanatory power on DC returns in the middle of 2021. On the second week of May 2021, for example, CBDCU explained 68.21% of the variation in DC. This might be explained by the findings of Bech and Garratt (2017), who stated that the central bank's decision to issue CBDC might lead to financial risk in the financial system and real economy. On average, SP shocks explained 13.6% of the variation in Bitcoin returns (DC) over the investigation period. While SP shocks sometimes had significant explanatory power, their contribution was more volatile. SP shocks accounted for a considerable amount of the variation in DC shocks, at 66.76%. At the same time, the portion explained by DC's own shock was 25.24% during the second week of January 2015. These variables had the highest explanatory power, at 72.07%, in the first week of March 2020, which coincides with the COVID-19 lockdown. The explanatory power of VIX shocks is quite low throughout the period, at approximately 1% of the changes in DC. However, it explains 39.73% of the changes in DC in the third week of March 2020. In the same period, the explanatory power of UCRY is 12.65%, while the explanatory power of UCRY's own shocks is estimated at 36.49%.

The contribution of UCRY shocks to Bitcoin returns is more stable than the rest of the variables, explaining, on average, 12.29% of the changes. However, these shocks account for the most critical portion of the changes in DC, along with CBDC news. For example, UCRY shocks explain 35.9% of the changes in DC in the first week of December 2021 before reaching the highest explanatory power in the second week of May 2021, at 68.50%. However, at the end of the investigation period, CBDCU still accounts for the largest portion of the variance in DC, at 33.65%, while DC's own shocks account for 30.18% of the forecast error variance. The evidence of the high influence of CBDC news shocks on Bitcoin returns is aligned with Scharnowski (2022) and Wang et al. (2023). Scharnowski (2022) analyzes cryptocurrency investors' reactions to central bank CBDC speeches and finds that CBDC speeches has an asymmetric and significant impact on the cryptocurrency markets. Wang et al. (2023) investigate the spillovers between the digital currencies attention index (CBDCAI) and cryptocurrency markets. Their findings confirmed that CBDCAI has a highly significant effect on cryptocurrency markets.

6. Concluding remarks

Continual financial innovation and the digitization of the economy have radically altered how individuals utilize money. In this context, CBDCs may become an indispensable monetary tool for central banks to conduct monetary policy and preserve financial stability. This paper examined the impact of the central bank digital currency news index on the financial and cryptocurrency markets based on this argument.

This paper contributed to the literature by analyzing the potential effects on the financial markets of introducing CBDCs. As CBDCs are relatively new instruments, most studies of the benefits and risks of implementing CBDCs have been theoretical, providing a fundamental qualitative analysis of CBDCs and their technological innovations (Wang et al., 2022). However, given the highly volatile nature of digital currency prices over time, one could argue that linear estimation methodologies may not be suitable for the identification of the dynamic linkages between CBDCs and financial cryptocurrency markets. Furthermore, our estimation sample contains significant developments in the cryptocurrency market, news about countries' attempts to implement CBDCs, and the COVID-19 pandemic, leading to a devastating decline in global economic activity. Based on this fact, this paper conducted time-varying impulse response and forecast decomposition analysis based on the estimation of a TVP-VAR model, including the CBDC Uncertainty Index, the cryptocurrency policy uncertainty index (UCRY), the S&P 500 index (SP), the VIX, and the Bitcoin price (DC) as endogenous variables.

The responses to CBDCU shocks obtained from the linear VAR are found to be statistically insignificant. The only exception is the cryptocurrency policy uncertainty index, which showed statistically significant positive responses. In contrast, the time-varying responses reveal that the direction and significance of the responses to CBDCU shocks vary markedly over time. The key finding of the study indicates that CBDC news have a negative and significant impact on the Bitcoin returns; this effect is especially more pronounced during the time there are increasing news reports on the adoption or development of the CBDCs by the central banks. Our results also reveal that CBDC news shocks have a positive and significant effect on cryptocurrency uncertainty, in line with the findings of Wang et al. (2022). Hence given those evidence, it is reasonable to draw the conclusion that the widespread adoption of CBDCs may help monetary policy authorities to regulate the bitcoin market and also conduct independent monetary policy. The evidence from the time-varying variance decomposition analysis support the results of time-varying responses as the CBDCU shocks account for a significant portion of the variation in UCRY shocks, particularly during the COVID-19 pandemic.

The findings of this study could help investors and policymakers to estimate the impact of CBDC news on the returns of cryptocurrencies. Further, investors can use our findings to hedge their risks better and restructure their investment portfolios. This paper also has several benefits for regulators and policymakers. For instance, it will help them to learn more about how CBDC news can influence the variation of cryptocurrency markets.

Our investigation has some limitations. First, CBDCs are still in the early stages of development, and there is insufficient data on the subject. Second, our research only examines how CBDC news affects the cryptocurrency market. More concrete results will be obtained after CBDC is widely used. Third, most published CBDC studies are theoretical, making it difficult to compare our findings to those studies. Finally, once the majority of central banks have adopted CBDCs, more research can be conducted to examine the effects of CBDCs on the functioning of monetary policy. As a result, this topic can be considered for further research area.

Data Availability

Data will be made available on request.

Appendix A

See the Appendix Table A1 and Figs. A1 and A2 here.

Table A1
Correlation between the variables.

	CBDCU	*CBDCA*	*SP*	*UCRY*	*VIX*	*DC*
CBDCU	1.000	0.916	0.743	0.891	0.116	0.710
CBDCA	0.916	1.000	0.759	0.862	0.115	0.651
SP	0.743	0.759	1.000	0.746	0.236	0.936
UCRY	0.891	0.862	0.746	1.000	0.215	0.686
VIX	0.116	0.115	0.236	0.215	1.000	0.227
DC	0.710	0.651	0.936	0.686	0.227	1.000

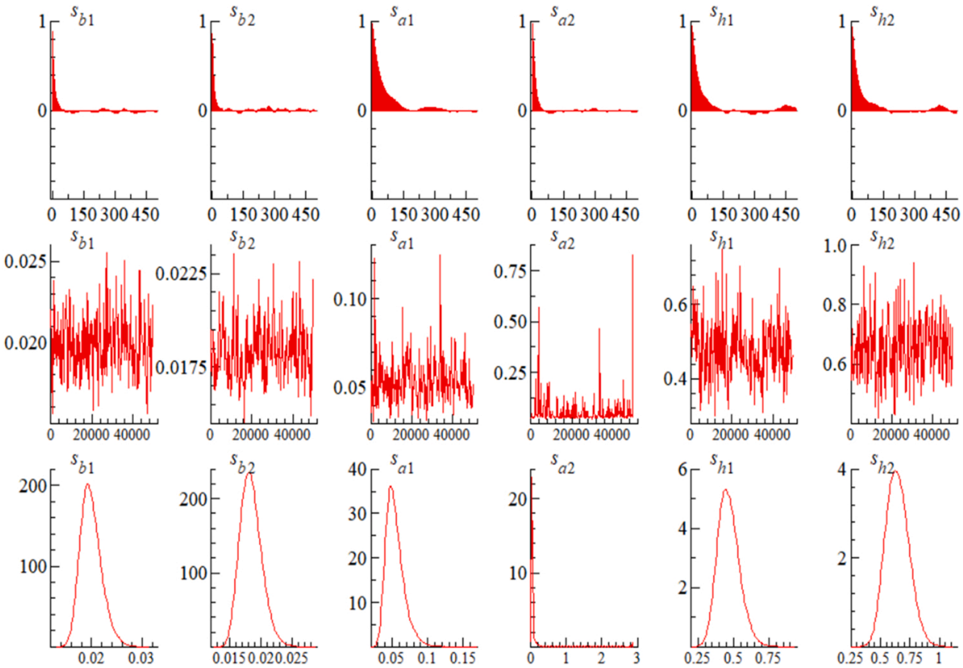
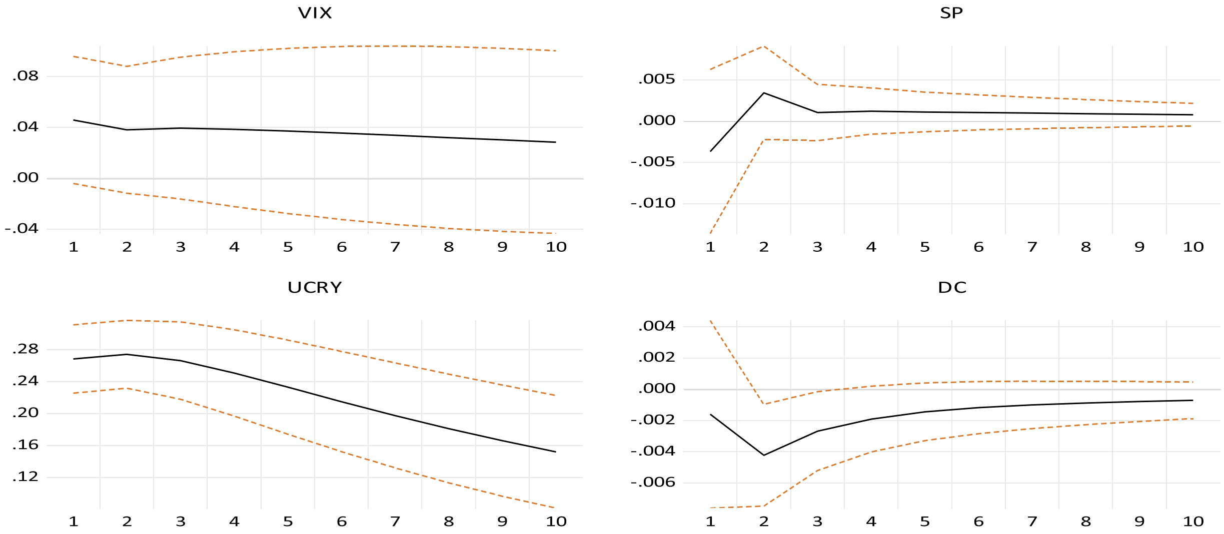
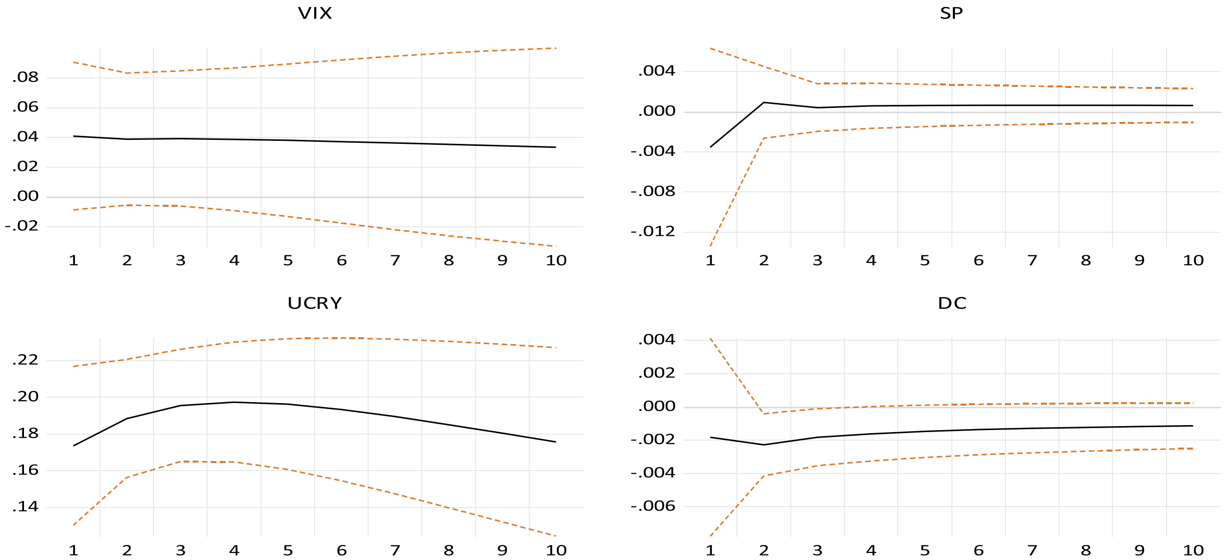


Fig. A1. Diagnostics for the TVP-VAR model.



a. Responses to Central bank digital currency uncertainty shocks (CBDCU)



b. Responses to Central bank digital currency attention shocks (CBDCA)

Fig. A2. Linear responses to CBDC news.

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