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Research article

Do different stock indices volatility respond differently to Central bank digital currency signals?

Wenjie Li[1] and Zimei Huang[2,*]

[1] School of Statistics and Mathematics, Guangdong University of Finance and Economics, Guangzhou 510320, China
[2] School of Economics and Statistics, Guangzhou University, Guangzhou 510006, China

* **Correspondence:** Email: 1112064001@e.gzhu.edu.cn.

Abstract: Central bank digital currency (CBDC) signals affect the volatility of stock indices in different sectors differently. This paper aims to examine whether the CBDC signal plays a role on the volatility of different stock indices. First, we employ a text analysis to compile the CBDC signal index, which spans from January 4, 2013 to March 16, 2023. Then, based on the mixing frequency data, we construct generalized autoregressive conditional heteroskedasticity mixed data sampling (GARCH-MIDAS) models to explore the various impacts of CBDC signal on the volatility of stock indices in different sectors. The findings show the heterogeneous effect of CBDC signals on the volatility of stock indices across different sectors. Furthermore, CBDC signals have a heterogeneous effect on the volatility of stock indices in different sectors for different lag periods.

Keywords: central bank digital currency signals; stock indices; GARCH-MIDAS model; heterogeneous effect

1. Introduction

Central bank digital currency (CBDC) signals exert different effects on stock indices of different sectors. The issuance of CBDC will have a profound impact on financial markets. On the one hand, the issuance of CBDC will change the traditional form of currency and payment methods. On the other hand, the circulation of CBDC will improve the efficiency and transparency of the financial system and reduce the cost of financial transactions. Besides that, CBDC signals have different effects on stock indices of different sectors. First, the CBDC signal helps to improve the efficiency and service quality of financial institutions, attract more investors, and bring a positive impact to the development of finance stocks. However, it may also reduce the profitability of traditional financial institutions such as banks [1], resulting in a decline in investor confidence in these institutions, thereby negatively affecting finance stocks. Second, the CBDC signal promotes fintech innovation and upgrading, and improves the profitability and market competitiveness of the fintech industry [2,3]. In addition, the CBDC signal promotes digital transformation and upgrading, providing better infrastructure and service support for the development of modern information technology [4–6]. Finally, the CBDC signal promotes the development of digital payment and other fields, providing more opportunities and market space for innovative enterprises, and promoting the rapid development of innovation and entrepreneurship. In summary, CBDC signals have different effects on stock indices of different sectors.

The impact of CBDC on the macro and micro economy has attracted much attention. On the one hand, CBDC exerts an impact on the macro-economy. First, Barrdear and Kumhof [7] explored the macroeconomics of CBDC. Because of the lower real interest rates, distortionary taxes, and monetary transaction costs, CBDC issuance of 30% of the GDP, against government bonds could permanently raise the GDP by 3% [8,9]. Second, the association between the informal economy and CBDC was investigated. Oh and Zhang [10] found that CBDC can decrease informality, though this effect becomes weaker in countries with larger informal economies. Third, the relationship between CBDC and credit supply was also explored. Kim and Kwon [11] examined the implications of CBDC for credit supply and financial stability and found that the introduction of deposits in CBDC account decreased credit supply by banks, raised the nominal interest rate and lowered a bank's reserve-deposit ratio. Andolfatto [12] assessed the impact of CBDC on private banks and found that it increased financial inclusion and diminished the demand for cash when the interest-bearing CBDC was introduced. Fourth, CBDC exert effects on the macroeconomic policy. For example, Xin and Jiang [13] constructed a dynamic stochastic general equilibrium model to indicate that the CBDC can eliminate the zero lower bound constraint and stabilize the economic fluctuations caused by a negative interest rate policy. Shen and Hou [14] investigated China's CBDC and its impacts on monetary policy and payment competition.

On the other hand, CBDC plays an impact on the micro-economy. First, CBDC News exerts an effect on financial markets. For instance, Wang et al. [15] constructed the CBDC Uncertainty Index and CBDC Attention Index based on coverage of over 660 million news stories from LexisNexis News & Business between 2015–2021 to explore the effects of CBDC News on financial markets. They found that CBDC indices play a significant negative impact on the volatilities of the MSCI World Banks Index, the United States Economic Policy Uncertainty Index, and the FTSE All-World Index, but a positive impact on the volatilities of cryptocurrency markets [16–18], foreign exchange markets [19,20], bond markets [21], the Cboe Volatility Index, and gold. Scharnowski [22] explored the cryptocurrency investors view about CBDC, and showed that prices react asymmetrically to the speeches, increasing more strongly after speeches that take a more positive stance. Li et al. [16] explored how the fintech sector reacts to CBDC signals released by central banks and found a positively time-varying response of the fintech sector to the CBDC signals. Second, the relationship between CBDC and bank earnings management was investigated. Ozili [23] investigated the role of CBDC in bank earnings management and found that CBDC-induced bank disintermediation leads to a reduction in bank deposits, a reduction in bank lending and a likely reduction in reported earnings [24], further leading banks to use accruals to manage earnings. Third, the impact of CBDC variation on the firm's implied volatility also raised concern, which was explored by Lee et al. [25]. They indicated that the positive impact of variation of CBDC on the implied volatility of the firm.

A great deal of literature concentrates on the influence factor of the volatility of the stock market. First, macroeconomic factors, such as business cycles [26–31], economic policy uncertainty [32–35] and so on, can cause the fluctuation of stock indices. Shi and Liu [36] employed a nonparametric quantile causality method to investigate the causal relationships between stock price fluctuation and the business cycle for the Brazil, Russia, India, China, South Africa (BRICS) countries. Arouri et al. [37] explored the impact of economic policy uncertainty on the stock market and found that an increase in policy uncertainty significantly reduces stock returns and the effect is stronger and persistent during extreme volatility periods. Second, the behavioral decisions of companies also affect the volatility of stock indices [38–42]. For example, Lau et al. [43] investigated emerging markets and found that a wider coverage of "realized" corporate corruption reduces the stock market volatility. In addition, personal factors such as investor sentiment can also cause the stock indices to fluctuate [44–49]. Chung et al. [50] examined the asymmetry in the predictive power of the investor sentiment in the cross-section of stock returns across economic expansion and recession states. When the investors' optimism increases, the return predictability of the sentiment should be most pronounced in an expansion state.

Although much literature has focused on the impact of CBDC and the influence factor of the volatility of the stock market, the following aspects can be further studied. First, the impact of CBDC signals on the stock market volatility can be further studied. Second, whether there are differences in how different stock indices volatilities respond to CBDC signals is worth exploring further. In addition, for different lag periods, whether CBDC signals have heterogeneous effects on the volatility of different stock indices are also need to be further investigated.

The contribution of this paper is to extend the literature on the relationships between the CBDC signals and stock indices volatilities. First, this paper constructs the generalized autoregressive conditional heteroskedasticity mixed data sampling (GARCH-MIDAS) model to explore how stock indices volatilities respond to the CBDC signals from an empirical perspective. Existing literature only explores the CBDC signals and fintech sector by employing the same frequency data model [16], which may lose the information of high-frequency data. However, we construct the mixed-frequency data model-GARCH-MIDAS model to explore the impact of CBDC signals on stock indices volatilities. The GARCH-MIDAS model allows us to better handle the links between stock indices volatilities, observed on a daily basis and CBDC signals that are sampled monthly. Second, we explore the heterogeneous effect of CBDC signals on four stock indices volatilities. The empirical findings show the heterogeneous effect of CBDC signals on the volatility of different stock indices. Furthermore, this paper further investigates the heterogenous impact of CBDC signals on the volatility of different stock indices for different lag periods. The results indicate that for various lag periods, CBDC signals have a heterogeneous effect on the volatility of stock indices in different sectors.

The rest of the paper is organized as follows. In Section 2, we describe the GARCH-MIDAS model, variables, data source and descriptive statistics. Section 3 reports the empirical results of the heterogenous impact of CBDC signals on the volatility of stock indices. The heterogeneous effects at different lag period are presented in Section 4. Section 5 presents the conclusion.

2. Method and variables

In this section, we provide a conceptual framework for our method, variables and data. The GARCH-MIDAS model is employed to investigate the heterogenous impact of CBDC signals on the different volatility of stock indices in Section 2.1. In addition, various measurements of CBDC signals and the different volatility of stock indices and their corresponding data source are presented in Section 2.2. Furthermore, descriptive statistics of variables are presented in Section 2.3.

2.1. GARCH-MIDAS model

In this paper, the GARCH-MIDAS model is employed to investigate the heterogenous impact of CBDC signals on the volatility of different stock indices. The mixed frequency data model outperforms the same traditional frequency data model, which maintains and uses the original data information, thereby avoiding the damage of data information under the influence of uncontrollable human factors. Moreover, it has comparative advantages in the accuracy of estimation results and prediction accuracy. The GARCH-MIDAS model, proposed by Engle and Rangel [51] and Engle et al. [52], is able to handle mixed-frequency data and incorporate low-frequency variables directly into the long-term component, and has been proven to be a powerful mixed frequency data model for analyzing the link between financial volatility and the macro-economy [53–55]. The GARCH-MIDAS model comprehensively considers the characteristics of monthly CBDC signals and different daily stock indices volatilities and takes the accuracy of low-frequency CBDC signals and the timeliness of the high-frequency volatility of different stock indices into account. Therefore, the GARCH-MIDAS model allows us to better handle the links between daily stock indices volatilities and monthly CBDC signals.

The GARCH-MIDAS model divides the conditional variance of the traditional GARCH model into two parts: the short-term volatility g_{it} and the long-term volatility τ_t. The short-term volatility g_{it} is driven by a GARCH process of stock indices volatilities, while the long-term volatility τ_t is given by the MIDAS regression of CBDC signals. Therefore, the GARCH-MIDAS model can be formally expressed, where the return of stock indices r_{it} on $i\ th$ day of $t\ th$ month is given as follows:

$$r_{it} = \mu + \sqrt{\tau_t * g_{it}} * \varepsilon_{it},\ \forall i = 1,2,\cdots,N_t \tag{1}$$

where the return of stock indices is represented as $r_{it} = 100 * \ln{(p_{it}/p_{(i-1)t})}$, p_{it} is the closing price on $i\ th$ day of $t\ th$ month. μ presents the conditional expectation of stock indices returns. τ_t and g_{it} represents the long-term and short-term volatility component, respectively. ε_{it} denotes the innovation term. N_t denotes the trading days of $t\ th$ month.

The short-term volatility component g_{it} follows the following GARCH (1,1) process:

$$g_{it} = (1 - \alpha - \beta) + \alpha * (r_{it} - \mu)^2/\tau_t + \beta * g_{(i-1)t} \tag{2}$$

where β denotes the degree of volatility clustering of the stock indices; the larger the β, the stronger the volatility clustering of the stock indices. Besides that, $\alpha > 0$, $\beta > 0$ and $\alpha + \beta < 1$.

The long-term volatility component τ_t is calculated by the following MIDAS regression:

$$\log{(\tau_t)} = m + \theta * \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) * X_{t-k} \tag{3}$$

where $\varphi_k(\omega_1, \omega_2)$ is a uncertain weight function, X_{t-k} denotes the CBDC signals, the coefficient θ indicates the influence of CBDC signals on stock indices volatilities, and K is the number of periods (time lags) for smoothing the long-term volatility. Following Engle and Rangel [48], the weighting scheme is assigned by the Beta function:

$$\varphi_K(\omega_1, \omega_2) = \frac{(k/(K+1))^{\omega_1 - 1} * (1 - k/(K+1))^{\omega_2 - 1}}{\sum_{j=1}^{K} (j/(K+1))^{\omega_1 - 1} * (1 - j/(K+1))^{\omega_2 - 1}} \tag{4}$$

where ω_1, ω_2 are the two parameters of the beta function. Considering the monotonically decreasing property of the weight function, we assume $\omega_1 = 1$. Therefore,

$$\varphi_K(1,\omega_2) = \frac{(1-k/(K+1))^{\omega_2-1}}{\sum_{j=1}^{K}(1-j/(K+1))^{\omega_2-1}} \tag{5}$$

where the sum of $\varphi_K(1,\omega_2)$ is equal to 1.

2.2. Variables and data source

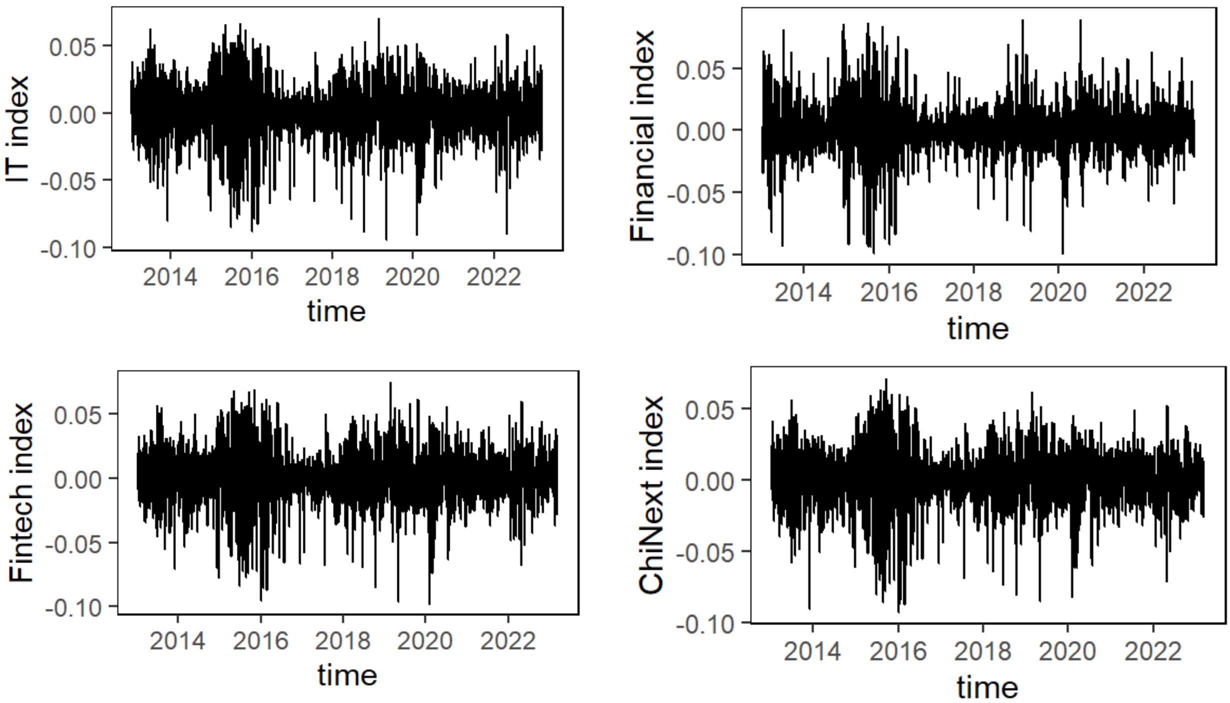
This analysis draws on the time series data of China spanning from 2013 to 2023. In this paper, there are two categories of data sampling: daily and monthly frequencies.

The daily data consists of four returns which are available from the CNI Indices website: the IT Index, Finance index, Fintech index and ChiNext Innovation indices. In the following empirical analysis, four stock indices are transferred to logarithm returns. The codes and samples of the four stock indices are presented in Table 1. The reasons of choosing these four stock indices are twofold. On the one hand, these four stock indices are closely linked to CBDC. On the other hand, these four stock indices, including finance, technology, fintech and innovation and entrepreneurship, have taken different responses to CBDC signals. Considering the availability of data, the sample period of these four stock indices spans from January 4, 2013 to March 16, 2023, with a total of 2,477 observations. Figure 1 presents the trends of the returns of the IT Index, Finance index, Fintech index and ChiNext Innovation index, respectively. As can be seen from Figure 1, the return trends for the four stock indices are heterogeneous. We can find heterogeneous price return movements across the four indices most of the time, indicating a high heterogeneity of stock markets.

The monthly data is the CBDC signal constructed by Li et al. [16]. The CBDC signal was obtained from the news of the People's Bank of China through text analysis method, which was developed in the following steps. First, they employed the Python crawler method to collect 1,000 information articles related to the CBDC from Baidu. Second, they used the demo keyword extraction method to extract the following 16 keywords associated with the CBDC from all information articles: CBDC, Digital Currency Electronic Payment (DCEP), digital RMB, digital currency, bitcoin, virtual currency, e-wallet, e-payment, cryptocurrency, e-cash, digital economy, digital finance, financial technology, cloud computing, blockchain, and online consumption. Third, they manually extracted news texts (excluding noisy texts, such as commemorative coin releases) from the press release page of the People's Bank of China website and summarize them by month. The original time frequency for news was daily; they converted it to a monthly frequency because there were numerous CBDC signals with zero values in the daily frequency. Fourth, they selected all sentences containing the keywords as "sentences related to CBDC" in the news texts. Fifth, they calculated the CBDC signal as monthly CBDC signal = monthly word number of relevant sentences/ monthly total number of words in the news. Their data spans from January 2012 to February 2022. In this paper, considering timeliness, we continued their calculation method to expand the sample to March 2023. Besides that, the four stock index data are available from 2013. Therefore, the CBDC signal covers the time horizon through January 2013 to March 2023, covering 123 months. Figure 2 presents the trend of CBDC signals.

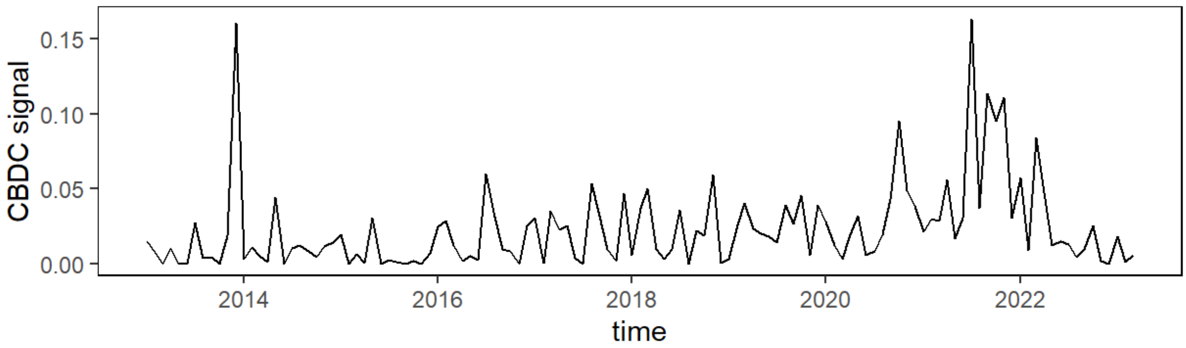
Table 1. The stock indices.

Index	Code	Sample
IT Index	399239	IT Index selects all non-ST and *ST Shenzhen A shares belonging to the information technology category.
Finance Index	399240	The Finance index selects all non-ST and *ST Shenzhen A shares belonging to the financial industry category.
Fintech	399699	The Fintech index is based on the sample of financial technology companies listed on the Shenzhen Stock Exchange and Shanghai Stock Exchange, and selects listed companies whose business fields belong to the financial technology industry and sub-sectors.
ChiNext Innovation	399018	The ChiNext Innovation index select the top 100 stocks in the ChiNext Market of the Shenzhen Stock Exchange.



Notes: The trends of four stock indices return for the entire sample period. From top to bottom, figures plot the returns of the IT Index, Finance index, Fintech index and ChiNext Innovation index, respectively. The data span from January 4, 2013 to March 16, 2023.

Figure 1. The trends of four stock indices return.



Notes: The trend of CBDC signal for the entire sample period. Monthly CBDC signal covers from January 2013 to March 2023.

Figure 2. The trend of CBDC signal.

2.3. Descriptive statistics

Table 2 reports the descriptive statistics of four stock indices returns and CBDC signals, where the data frequency, observations, mean, standard deviation, the minimum and maximum, range, skewness, kurtosis and J-B statistic are reported.

Table 2. Descriptive statistics.

Variable	IT	Finance	Fintec	Eninno	signal
Freq.	Daily	Daily	Daily	Daily	Monthly
Obs.	2477	2477	2477	2477	123
Mean	0	0	0.001	0.001	0.023
Std. dev.	0.021	0.02	0.021	0.02	0.029
Min	–0.095	–0.099	–0.098	–0.093	0
Max	0.071	0.09	0.075	0.071	0.164
Range	0.166	0.189	0.173	0.164	0.164
Skewness	–0.477	–0.076	–0.43	–0.615	2.557
Kurtosis	4.92	7.149	5.035	5.443	11.094
J-B	474.09***	1779.3***	503.61***	771.82***	9453.4***

Notes: (1) The reported descriptive statistics include the data frequency (Freq.), observations (Obs.), mean, standard deviation (Std. dev.), the minimum (Min) and maximum (Max), Range, Skewness, Kurtosis and J-B statistic of the return of IT index (IT), Finance index (Finance), Fintech index (Fintec), Entrepreneurship and innovation index (Eninno) and CBDC signal. (2) The sample of four indexes span from January 4, 2013 to March 16, 2023 and CBDC signal covers from January 2013 to March 2023. (3) ***, **, * denote the null hypothesis is rejected at 1, 5, 10% statistical significance level respectively.

As shown in Table 2, the mean of four stock indices return time series were almost zero, while the mean of the IT Index and the Finance index were 0, and the mean of the Fintech index and the ChiNext Innovation indices were 0.001. This is similar to the standard deviation of these four stock indices returns. However, the range shows that the return of the four indices are heterogenous. Besides that, it is obvious that the skewness of the four stock indices return are negative, implying that the four stock indices returns are left-skewed. Additionally, the skewness of the CBDC signal is positive, indicating that the CBDC signal is right skewed. From the kurtosis of all five variables, we know that the five variables are leptokurtic. Furthermore, the Jarque–Bera (J-B) statistics results also indicate that these four stock indices returns and CBDC signals are not normally distributed at the 1% significance level.

3. Empirical results

In this section, we investigate the heterogeneous effect of CBDC signals on the volatility of stock indices across different sectors. First, we conducted the unit root and autocorrelation tests of the IT Index, Finance index, Fintech index, ChiNext Innovation indices and CBDC signal. Then, we construct a GARCH-MIDAS model to explore the heterogeneous effect of CBDC signals on different stock indices.

Table 3. Unit root and autocorrelation tests.

Variable	ADF	Q(8)	BP
IT	−13.185***	22.142***	652.300***
Finance	–12.708***	26.630***	614.740***
Fintec	–13.269***	17.123**	725.930***
ChiNext	–13.357***	16.503**	899.680***
signal	–8.1137***	14044***	14449***

Notes: (1) This table reported the unit root and autocorrelation test results, which include Augmented Dickey-Fuller unit root test (ADF), Ljung–Box test (Q(8)) and Box-Pierce test (BP) of the return of IT index (IT), Finance index (Finance), Fintech index (Fintec), Entrepreneurship and innovation index (ChiNext) and CBDC signal. (2) The sample of four indexes span from January 4, 2013 to March 16, 2023 and CBDC signal covers from January 2013 to March 2023. (3) ***, **, * denote the null hypothesis is rejected at 1, 5, 10% statistical significance level respectively.

Table 3 presents the results of the unit root and autocorrelation tests. First, we used the ADF test to verify the stationary of five variables. From Table 3, the ADF test of all variables reject the null hypothesis at a 1% significance, which proved that five series are all stationary. Besides that, the Ljung–Box statistics and Box-Pierce test are all significant at the 1% significance level, which rejects the null hypothesis of no autocorrelation, indicating that all variables have a strong autocorrelation. Therefore, we further adopt the GARCH- MIDAS model to explore the heterogenous impact of the CBDC signal on the volatilities of different stock indies.

In this section, we employ the GARCH-MIDAS model to quantitatively capture the impacts of the CBDC signal on the volatilities of four stock indies. Table 4 presents the estimation results of GARCH-MIDAS model at lag periods $K = 24$.

CBDC signals have a heterogeneous effect on the long-term volatility of stock indices across different sectors. As an example, while observing the 24-month lag, the CBDC signal has a significant negative impact on the long-term volatility of the IT and ChiNext Innovation indices, but has no significant impact on the long-term volatility of the Financial and Fintech indices. First, apart from μ, most of the estimated coefficients are significant, indicating that the GARCH-MIDAS model fits the volatility of the four stock indices well. Second, all the values of α and β are significantly different from 0 at the 1% significance level, and the sum of α and β for all stock indices are close but less than 1, which implies the short-term volatility of the four stock indices returns have clustering features. Third, CBDC signals have a heterogeneous impact on the long-term volatility of stock indices returns across different sectors. The parameter θ indicates the impact of the CBDC signal on the long- term volatility of the stock index return. As can be seen in Table 4, the parameter θ of IT and ChiNext are negative and significant at the 5 and 10% level, respectively. The results indicate that CBDC signals play a negative impact on the long-term volatility of IT stock indices returns and Innovation and Entrepreneurship Stock Index return. However, the θ of finance and fintech are insignificant at the 10% level, which implies that the impact of CBDC signals on the long-term volatility of financial indices returns and fintech indices returns are insignificant. These findings present strong evidence that CBDC signals have a heterogeneous influence on the volatilities of different stock indices returns.

Table 4. Results of Garch Midas model (K = 24).

	IT	Finance	Fintec	ChiNext
μ	–0.019 (0.040)	–0.003 (0.036)	0.000 (0.102)	0.017 (0.038)
α	0.049*** (0.017)	0.050*** (0.016)	0.048*** (0.014)	0.055*** (0.017)
β	0.935*** (0.025)	0.936*** (0.021)	0.936*** (0.021)	0.929*** (0.024)
m	1.525*** (0.216)	1.098*** (0.279)	1.528*** (0.231)	1.366*** (0.220)
θ	–7.841** (3.977)	5.190 (5.785)	–7.117 (5.136)	–7.179* (3.815)
ω_2	19.139** (7.667)	1.000 (1.587)	13.208* (7.469)	18.853** (7.916)

Notes: (1) This table reports the parameter estimates of all four models when the lag period K = 24. (2) The numbers in the parentheses are the standard deviation. (3) ***, ** and * denote the significance levels at 1, 5 and 10% respectively.

We further employed the asymmetric Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) MIDAS model to capture the asymmetric impacts of the CBDC signal on the volatilities of four stock indices. Table 5 shows the estimation results of the asymmetric GJR-GARCH MIDAS model at lag periods K = 24.

The leverage effect of CBDC signals on the long-term volatility of different stock indices are insignificant. From Table 5, all the values of α and β are significantly different from 0 at the 1% significance level, and the sum of α, β and $\gamma/2$ for all stock indices are close but less than 1, which implies the short-term volatility of the four stock indices returns have clustering features. Besides that, the coefficients of γ are insignificant, which indicate that the leverage effect of CBDC signals on the long-term volatility of different stock indices are insignificant. These findings present strong evidence that CBDC signals have an insignificant leverage effect of CBDC signals on the long-term volatility of different stock indices.

Table 5. Results of asymmetric GJR-GARCH MIDAS model (K = 24).

	IT	Finance	Fintec	ChiNext
μ	−0.026	–0.007	–0.008	0.008
	(0.039)	(0.036)	(0.040)	(0.037)
α	0.044***	0.046***	0.042***	0.045***
	(0.012)	(0.016)	(0.011)	(0.012)
β	0.921***	0.934***	0.922***	0.919***
	(0.036)	(0.024)	(0.031)	(0.031)
γ	0.027	0.010	0.029	0.031
	(0.030)	(0.020)	(0.030)	(0.027)
m	1.571***	1.217***	1.596***	1.364***
	(0.231)	(0.237)	(0.272)	(0.232)
θ	–8.914**	0.699	–8.468	–7.216*
	(4.481)	(1.265)	(6.682)	(4.205)
ω_2	17.945**	1.000	11.977	17.269**
	(7.368)	(1.832)	(9.534)	(8.098)

Notes: (1) This table reports the parameter estimates of asymmetric GJR-GARCH MIDAS model when the lag period K = 24. (2) γ is the coefficient to quantify the volatility leverage effect. (3) The numbers in the parentheses are the standard deviation. (4) ***, ** and * denote the significance levels at 1, 5 and 10% respectively.

4. Heterogeneous effects at different lag period

In this section, we further investigate the heterogeneous effect of CBDC signals on the volatility of stock indices across different sectors at different lag periods. Table 6 present the results of the GARCH-MIDAS model at different lag periods. Panel A, B and C in this table reports the parameter estimates of all four models when the lag period K = 3, 6 and 12, respectively.

For different lag periods, CBDC signals exerts a heterogeneous impact on the long-term volatility of different stock indices. Specifically, when lagging for 3 months, CBDC signals only have a significant negative impact on the long-term volatility of the financial stock indices. First, apart from μ, most of the estimated coefficients are significant, indicating that the GARCH-MIDAS model fits the volatility of the four stock indices well for a lag period of 3. Second, all the values of α and β are significantly different from 0 at the 1% significance level, and the sum of α and β for all stock indices are close but less than 1, which implies the short-term volatility of four stock indices returns have clustering features for a lag period of 3. Third, CBDC signals have a heterogeneous impact on the long-term volatility of the stock indices return across different sectors for a lag period of 3. As can be seen in Table 6, the parameter θ of Finance stock indices are negative and significant at the 1% significance level. The results indicate that CBDC signals play a negative impact on the long-term volatility of Finance stock indices returns. However, the θ of IT, Fintech and ChiNext stock indices are insignificant, which implies that the impact of CBDC signals on the long-term volatility of IT stock indices returns, Fintech stock indices returns and Innovation and Entrepreneurship stock index returns are insignificant. In conclusion, CBDC signals have a heterogeneous influence on the volatilities of different stock indies returns for a lag period of 3.

Table 6. Results of GARCH-MIDAS model at different lag periods

	μ	α	β	m	θ	ω_2
Panel A: K = 3						
IT	0.012	0.045***	0.940***	1.406***	–3.872	2.337**
	(0.037)	(0.012)	(0.018)	(0.184)	(2.853)	(0.951)
Finance	0.020	0.056***	0.927***	1.317***	–3.119*	20.409
	(0.033)	(0.016)	(0.021)	(0.195)	(1.854)	(19.951)
Fintec	0.028	0.034***	0.966***	–0.180	–3.405	1.571
	(0.043)	(0.010)	(0.009)	(0.932)	(3.370)	(0.975)
ChiNext	0.035	0.048***	0.937***	1.274***	–3.610	3.023*
	(0.035)	(0.012)	(0.018)	(0.181)	(2.527)	(1.682)
Panel B: K = 6						
IT	0.006	0.046***	0.940***	1.302***	0.922***	1.000*
	(0.037)	(0.012)	(0.017)	(0.159)	(0.328)	(0.521)
Finance	0.021	0.057***	0.926***	1.322***	–3.096	26.216
	(0.033)	(0.015)	(0.020)	(0.198)	(1.917)	(49.861)
Fintec	0.028	0.049***	0.935***	1.458***	–4.173	2.936**
	(0.037)	(0.011)	(0.017)	(0.200)	(4.391)	(1.354)
ChiNext	0.032	0.050***	0.935***	1.324***	–5.267	3.541*
	(0.035)	(0.012)	(0.017)	(0.193)	(3.455)	(1.990)
Panel C: K = 12						
IT	0.004	0.054***	0.929***	1.566***	–9.756**	7.682***
	(0.037)	(0.012)	(0.017)	(0.203)	(4.218)	(2.820)
Finance	0.018	0.045***	0.955***	–0.160	–12.554	4.386
	(0.043)	(0.015)	(0.012)	(3.316)	(13.672)	(6.629)
Fintec	0.023	0.051***	0.931***	1.575***	–8.454*	6.740**
	(0.038)	(0.011)	(0.016)	(0.204)	(4.698)	(3.259)
ChiNext	0.031	0.055***	0.929***	1.397***	–8.326**	9.330**
	(0.034)	(0.013)	(0.017)	(0.205)	(3.942)	(4.684)

Notes: (1) The Panel A, B and C in this table reports the parameter estimates of all four models when the lag period K = 3, 6 and 12, respectively. (2) The numbers in the parentheses are the standard deviation. (3) ***, ** and * denote the significance levels at 1, 5 and 10% respectively.

When lagging for 6 months, CBDC signals only have a significant positive impact on the long-term volatility of the IT stock indices. First, apart from μ, most of the estimated coefficients are significant, indicating that the GARCH-MIDAS model fits the volatility of the four stock indices well for a lag period of 6. Second, all the values of α and β are significantly different from 0 at the 1% significance level, and the sum of α and β for all stock indices are close but less than 1, which implies the short-term volatility of four stock indices returns from the GARCH-MIDAS model have strong volatility clustering for a lag period of 6. Third, CBDC signals have a heterogeneous impact on the long-term volatility of stock indices returns across different sectors for a lag period of 6. As can be seen in Table 6, the parameter θ of IT stock indices are positive and significant at the 1% significance level. The results indicate that CBDC signals play a positive impact on the long- term volatility of IT stock indices returns. However, the θ of Finance, Fintech and ChiNext stock indices are insignificant at the 10% level, which implies that CBDC signals exert insignificant impacts on the long-term volatility of Financial stock indices returns, Fintech indices returns and Innovation and Entrepreneurship stock index returns. These findings show that CBDC signals have a heterogeneous influence on the volatilities of different stock indices returns for a lag period of 6.

When lagging for 12 months, CBDC signals have a significant negative impact on the long-term volatility of the IT, Fintech and ChiNext Innovation stock indices. First, apart from μ, most of the estimated coefficients are significant, indicating that the GARCH-MIDAS model fits the volatility of the four stock indices well for a lag period of 12. Second, all the values of α and β are significantly different from 0 at the 1% significance level, and the sum of α and β for all stock indices are close but less than 1, which indicates the short-term volatility of the four stock indices returns from the GARCH-MIDAS models have strong volatility clustering for a lag period of 12. Third, CBDC signals have a heterogeneous impact on the long-term volatility of stock indices returns across different sectors for a lag period of 12. As can be seen in Table 6, the parameter θ of IT and ChiNext stock indices are negative and significant at the 5% level. The results indicate that CBDC signals play a negative impact on the long-term volatility of IT stock indices returns and innovation and entrepreneurship stock index returns. The parameter θ of Fintech stock indices are negative and significant at the 10% significance level, indicating the negative effect of CBDC signals on the Fintech stock indices returns. However, the θ of Finance stock indices are insignificant, which implies that the impact of CBDC signals on the long-term volatility of financial stock indices returns is insignificant. These findings strongly indicate that CBDC signals have a heterogeneous influence on the volatilities of different stock indices returns for a lag period of 12.

To sum up, CBDC signals exert a heterogeneous impact on the long-term volatility of different stock indices returns for different lag periods.

5. Conclusions

Based on the mixing frequency data, including monthly CBDC signals and daily different stock indices, this paper constructs the GARCH-MIDAS model to examine whether the CBDC signal plays various impact on different stock indices. The mixing frequency data spans from January 2013 to March 2023. And we yield the following conclusions.

First, CBDC signals have a heterogeneous effect on the long-term volatility of stock indices across different sectors. Specifically, taking a lag of 24 months as an example, the CBDC signal has a significant negative impact on the long-term volatility of the IT and entrepreneurship sector indices; however, it has no significant impact on the long-term volatility of the financial and fintech indices.

Second, for different lag periods, CBDC news has a heterogeneous impact on the long-term volatility of different sector stock indices. Specifically, when lagging for 3 months, CBDC signals only have a significant negative impact on the long-term volatility of the financial sector index. When lagging for 6 months, CBDC signals only have a significant positive impact on the long-term volatility of the IT sector index. When lagging for 12 months, CBDC signals have a significant negative impact on the long-term volatility of the IT, Entrepreneurship and Fintech sector indices. When lagging for 24 months, CBDC signals have a significant negative impact on the long-term volatility of the IT and Entrepreneurship Sector indices.

Future research could be conducted on at least two fronts. On the one hand, future research can include more economic variables such as investor sentiment to predict the Chinese stock indices volatilities. On the other hand, future study can focus on whether CBDC signals of other emerging or developed countries exert heterogeneous effect on the long-term volatility of their various stock indices.

Use of AI tools declaration

The authors declare they have not used artificial intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare there is no conflict of interest.

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