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Can digital economic attention spillover to financial markets? Evidence from the time-varying Granger test

Xiaohang Ren [a], Jingyao Li [a], Yukun Shi [b,*]

[a] School of Business, Central South University, Changsha, 410083, China
[b] Adam Smith Business School, University of Glasgow, Glasgow, G12 8QQ, UK

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ABSTRACT

The digital economy is pervasive, all-encompassing, and a pan-industrial revolution. This paper pioneers constructing a digital economy concern index by extracting the web search volumes of keywords through crawler technology and analyzes the dynamic causal relationship with the Chinese stock markets via time-varying Granger tests. The results reveal that digital economy attention has a significant predictive effect on stock prices in a time-varying pattern and that the causal spillover varies across industry segments, with higher success rates and longer duration of causal detection under recursive algorithms. Moreover, the causal impact of digital economy attention on stock prices is generally limited in sluggish market states, mainly reflected during the COVID-19 pandemic and again after the epidemic had passed for some time with significant causality. This paper provides new evidence and analytical perspectives on the performance of the digital economy in financial markets, informing the digital transformation of various industries and investment decisions of investors.

1. Introduction

With the continuous development of modern information technologies such as the Internet of Things, big data, and artificial intelligence, the digital economy is becoming a pivotal variable in reorganizing global factor resources, reshaping the global economic structure, and reconstructing the global competition landscape (Pan et al., 2022). Scholars have widely recognized that the value connotation of digital activities has been incorporated into the stock value (Chen and Srinivasan, 2019; Shi et al., 2022), which has not only reversed the traditional operation mode of various industries but also fundamentally changed the expectations and behaviors of market participants (Peter et al., 2021). In addition, relying on the symbiotic relationship in which finance acts as the bloodline to serve the economy, the digital economy is inseparable from the financial market. Especially in the context of the ongoing fourth industrial revolution in full swing, the digital economy is expected to become a new strategic highland and infiltrate the structural issues of the financial space through digital technology, thereby accelerating the overall integration with the financial market and further enhancing the productivity, profitability, and competitiveness of the entire industry (Adekoya et al., 2022).

Specifically, financial activities firstly can guide the direction of capital flow (Liew et al., 2022) to solve the financing needs of the digital economy and achieve optimal allocation of funds. Second, the financial market has the functions of information aggregation and price discovery, and the information feedback mechanism and price changes of the financial market can reflect the development of the digital economy industry. Based on this, it can be seen that the digital economy and the financial market are inherently related. In

* Corresponding author.
E-mail addresses: domrxh@outlook.com (X. Ren), yukun.shi@glasgow.ac.uk (Y. Shi).

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particular, in terms of the relationship between the digital economy and the company's stock price, on the one hand, enterprises can create and distribute new business value through the superposition and multiplication of data productivity and the all-encompassing, chain-wide transformation of traditional industries by new Internet technologies (Schallmo et al., 2017; Li et al., 2022). On the other hand, the digital transformation of companies can increase equity liquidity through various channels, such as ameliorating information asymmetry, reinforcing positive market expectations, and boosting corporate R&D investment and innovation output, which in turn affects equity prices. Therefore, the digital economy and stock market performance are also inextricably linked. However, there has been no multidisciplinary discussion on their associations, and this paper aims to fill this research gap.

In addition to a series of economic or non-economic events that can have spillover effects on the stock market (Iwanicz-Drozdowska et al., 2021; Ren et al., 2022), investor attention has also been identified in behavioral finance research as a momentous factor in determining and predicting financial market performance (Chen and Lo, 2019). Especially in the current environment of massive information, the efficiency of information dissemination and the level of investor attention will be related to the effective allocation of capital market resources and market dynamics (Meng and Zhang, 2022; Wang et al., 2022). The microscopic behavior of individuals is the source of macroscopic phenomena in financial markets. As the main participants in market transactions, investors' psychological cognition, preference, and attention to the market will affect price fluctuations to varying degrees. Since De Long et al. (1990) revealed that noise traders make investment decisions based on emotion, which can lead to excessive volatility in asset prices and expected returns, investor attention has gradually been studied as a cognitive resource. However, little is known about the predictive performance of digital economy attention on market prices. Therefore, when investigating the impact of the digital economy on the financial market, this paper takes investors' attention as the point of penetration, hoping to serve as a beneficial expansion of the existing literature.

In the empirical studies of investor attention, the keyword-based online search data not only exerts the function of retrieving information but also records the investor's search behavior, so it can directly and effectively insinuate the investor's cognition and transaction expectations. Da et al. (2009) took the lead in using the Google Trends index as a proxy for investor attention and explored its stock forecasting capabilities, and then scholars have successively conducted research on its relationship with individual stocks and the overall market (Bijl et al., 2016; Swamy et al., 2019). Domestically, the Baidu Index is widely favored by scholars for its high-precision advantage of daily data and high market share (Fang et al., 2020; Huang et al., 2017). Hence, this paper uses the crawler technology and principal component analysis (PCA) method to construct the digital economy attention indicator based on the keywords of the Baidu index and analyzes how the impact of digital economy on the financial market is transmitted through sentiments.

The intimate nexus of investor attention and financial markets have been fully acknowledged by the academic community, with an intriguing section exploring the causality between them (Chen and Chen, 2022; Li et al., 2019). However, the commonality of this causality-based literature is the use of a static Granger framework, which has limitations in extracting time-varying interaction features. Inspired by Zhao et al. (2020)'s view that the interaction between markets will be affected by investors' behaviors and produce time-varying spillover effects, this paper argues that the spillover of digital economy attention to financial markets also has the characteristics of multiple time scales, because economic conditions and financial environments are constantly changing over time (Jammazi et al., 2017). Accordingly, we apply the novel time-varying Granger technique introduced by Shi et al. (2018, 2020) to achieve the real-time detection of causation and accurate identification of such relationships' occurrence and collapse dates. In addition, locating the time path of causal spillovers between digital economy attention and financial markets can be a powerful aid to investors' price forecasting and portfolio optimization. Meanwhile, understanding the dynamic evolution of their interactions is particularly important for companies to lay out their strategic vision of digitalization and to develop scientific digital transformation policies at specific times.

The Chinese market is an ideal environment for this research. On the one hand, China is the world's second-largest digital economy and the largest emerging market for digital development (Zeng et al., 2022). The size of China's digital economy continues to climb and, as a stabilizer and accelerator of the national economy, has become a new engine driving the country's high-quality economic development, thus creating a favorable environment for digital research. On the other hand, the Chinese stock market is well-suited for studying attention. Specifically, the Chinese stock market is dominated by retail investors, whose limited cognitive ability is prone to social group rational deviations (Cai et al., 2022). In addition, compared with the mature securities markets in the West, China's financial market is still not completely efficient, so financial anomalies such as stock prices skyrocketing and falling have become the norm, which easily leads to information hype and speculation in the market. Therefore, it is of practical significance to explore the impact of the digital economy attention on the financial market.

The contribution of this paper to the existing literature is manifested in the following aspects: First, this is the groundbreaking work that extracts the online search volume of keywords related to the digital economy and constructs a comprehensive index of the digital economy through the PCA method to characterize the investor's attention and perception of the digital economy. Second, we not only analyze the macro-financial market but also subdivide the causal associations between the digital economy and stock prices from the micro perspective and industry operation characteristics, which helps enrich the understanding of the digital transformation interactive model with the enterprise. This new exploration and expansion of research related to the digital economy opens the “black box” of mechanisms between digital transformation and stock market performance. Third, this paper uses online attention as a starting point to reveal the spillover mechanism of investor sentiment on stock price volatility, which is conducive to a more rational investment allocation decision by investors and a deeper grasp of the industry's digital transformation by enterprises. Fourth, the time-varying Granger method used in this paper pinpoints the time path of causal spillovers between digital economy attention and financial markets, and provides a profound dissection of their dynamic nexus from different time domains, offering policy insights for both corporate policymakers and financial investors.

The remainder of the article is structured as follows: Section 2 provides a brief overview of the relevant literature; Section 3 introduces the methods involved in this paper; Section 4 describes indicator construction and datasets; Section 5 analyzes the empirical results; Section 6 concludes and supplies policy recommendations.

2. Literature review

The digital economy as a manifestation of the new economy has been defined by international organizations, academics, and practitioners with differing views. The digital economy was first introduced by Tapscott (1996) as an economic system that extensively uses intelligence and communication technologies. After entering the 21st century, research on the digital economy has seen a spurt of growth, with the 2016 G20 Initiative on Digital Economy Development and Cooperation defining its connotations around crucial factors of production, important vectors, and effective drivers of the digital economy (G20 Research Group, 2016). Moreover, Zhen et al. (2021) consider the digital economy to be economic activities related to communication technologies, digital knowledge, and Internet information. Along with the clarification of the definition of the digital economy, the impact of the digital economy on productivity, economic development, and business performance has stimulated a wide range of scholarly attention. It has yielded significant breakthroughs and plentiful achievements. Within this rise, digital infrastructure (Zoppelletto and Orlandi, 2022), technological innovation (Sahut et al., 2022), and online platforms (Xie et al., 2022) play a decisive role.

For instance, Gaglio et al. (2022) argued that digital transformation positively affects labor productivity gains, with technological innovation mediating. Using the dynamic spatial Durbin model, Gu et al. (2022) found that the level of digitization is conducive to the improvement of green total factor productivity through the three mechanisms of capital, structure, and technology. Many scholars link digitalization to economic growth. Pradhan et al. (2015) suggested that digital infrastructure positively affects economic growth in the long run for the Asian region. Pradhan et al. (2019)'s additional study of his views concluded that improving communication infrastructure contributes to economic growth through a long- and short-term causality test by selecting the European region as a representative. Regarding the impact of the digital economy on business performance, most existing literature revolves around the two channels of digital inclusion and fintech, with mixed results. Through the generalized moment method, Wu and Huang (2022) indicated that digital inclusive finance is efficient in improving the financial performance of companies, particularly non-state and small firms. Conversely, the findings of the study by Chen et al. (2022) reported a negative impact between digital financial inclusion and the productivity of listed companies, attributing it to its ineffectiveness in alleviating corporate financing constraints. Among other studies, Abbasi et al. (2022) elucidated the role of fintech in contributing to the efficiency of SMEs, while Xie and Zhu (2022) took the opposite view, revealing that the inefficiency dilemma faced by fintech in corporate capital allocation is due to blocked debt financing. Based on the above discussion, we can find that studies investigating the impact of the digital economy on macroeconomic development and financial market performance through the channels of capital, technology, and infrastructure are commonplace. Still, no scholar has yet explored the spillover linkages of the digital economy on the Chinese stock market from the perspective of investor attention, which forms the motivation for this paper.

It is noteworthy that the current climate issue is widely discussed, and sustainable development is the trend of the times. Against this backdrop, the nexus of the digital economy, energy markets, and green development has also become the research focus. On the one hand, the discussion of the interaction between the digital economy and the energy market mainly involved energy efficiency (Bastida et al., 2019; Zhang et al., 2022a), low carbon development (Li and Wang, 2022; Zhang et al., 2022b; Ren et al., 2023) and energy transition (Moritz Loock, 2020; Nijhuis et al., 2015). The consistent conclusion of these studies is that the digital economy is beneficial for energy efficiency and serves as an important driver of low-carbon development. In contrast, consensus on the impact of the digital economy on the energy transition has yet to be reached. Specifically, Shahbaz et al. (2022) claimed that the digital economy could stimulate the energy transition and expand the share of renewable energy. However, Murshed et al. (2020) held a negative attitude toward the role of digital technology in improving the renewable energy mix through their research on South Asian economies. Veskioja et al. (2022) also demonstrated that digital applications still lag behind in achieving the energy transition. On the other hand, concerning literature related to the digital economy and green development, the main focus is on green technology innovation (Lin and Ma, 2022) and green total factor productivity (Gu et al., 2022), in which the positive role played by the digital economy is prevalent in the conclusions. Although the digital economy has been extensively researched, the spillover effects of the digital economy on financial markets and its ability to forecast stock prices have been somewhat ignored.

Studies on the digital economy has generally measured the level of development of the digital economy from a multidimensional perspective (Xue et al., 2022), with few starting with digital economy attention. Consequently, this paper aims to build on this research gap to achieve a useful extension of existing research. The existing literature has shown that financial market performance may be related to different forms of investor sentiment or attention. In particular, the predictability of investor attention on stock returns has generally been well-established in behavioral finance. For example, the key role of attention in predicting stock returns was confirmed by Yuan et al. (2022) through an investigation of the attention of local and non-local retail investors. Zhang and Li (2021) supplemented their findings with several models that are robust to structural breaks, and found that stock return prediction models that incorporated investor attention are more accurate. Further quantitative analysis by Cai et al. (2022) concluded that investor attention negatively affects stock returns by driving trading behavior, however Ballinari et al. (2022) reported the opposite result, suggesting that the attention of retail investors has a positive impact on the volatility of stock returns.

Regarding metric measures of attention, Google and Baidu search indices are often considered direct proxies in the empirical literature. Analysis by Joseph et al. (2011) noted that high Google search volume tends to lead to positive stock returns and that stocks with different return volatility and arbitrage difficulty have different sensitivities to search intensity. In addition to predicting stock returns, Prange (2021) observed that Google search-based investor attention is a significant determinant of financial asset co-movement, while facilitating portfolio hedging effectiveness. In the case of the Chinese market, the Baidu index is widely used for its universality and superiority. Fang et al. (2020) pointed out that the Baidu index search volume can effectively improve the prediction of Chinese stock market volatility via the GARCH model. Zhao (2019)'s findings were consistent with their conclusions, further indicating that the Baidu search index is positively correlated with stock performance. Unfortunately, empirical assessment of the impact of digital economy attention on financial markets is limited, and this paper attempts to break this impasse by extracting a series of keyword search data related to the digital economy based on the Baidu index.

3. Methodology

3.1. Principal component analysis

Big data is high-dimensional. The principal component analysis is a multidimensional statistical method for dimensionality reduction and multidimensional data visualization, which centers on transforming one or more sets of indicators that may have some degree of correlation into a number of uncorrelated principal component variables through an orthogonal transformation, so that the original data has the largest range of change along this direction (Troccoli et al., 2022). The advantage of the PCA method is that it can convert the messy raw data into a low-dimensional variable system with high precision to achieve the purpose of dimensionality reduction and decoupling, while reducing noise redundancy and information loss (Roden et al., 2015). Therefore, since Hotelling (1932) established a canonical PCA method and principles using the derived patterns, it has been widely used in fields such as index construction, pattern recognition, etc. In addition, PCA is a common method of constructing indicators based on objective weighting, where the information contained in the principal components is uncorrelated. That is, the repeated information in each indicator is superimposed on one of the principal components, thus achieving the purpose of analyzing the problem with a few principal components instead of the original ponderous indicators.

Suppose **X** is the original dataset with high signal-to-noise ratio, and **Y** is the re-representation of the original dataset after transformation by rotation matrix **P**.

$$\boldsymbol{Y} = \boldsymbol{P}\boldsymbol{X} = \begin{bmatrix} \boldsymbol{p}_1 \\ \vdots \\ \boldsymbol{p}_m \end{bmatrix} \bullet [\boldsymbol{x}_1 \quad \cdots \quad \boldsymbol{x}_n] = \begin{bmatrix} \boldsymbol{p}_1 \bullet \boldsymbol{x}_1 & \cdots & \boldsymbol{p}_1 \bullet \boldsymbol{x}_n \\ \vdots & \ddots & \vdots \\ \boldsymbol{p}_m \bullet \boldsymbol{x}_1 & \cdots & \boldsymbol{p}_m \bullet \boldsymbol{x}_n \end{bmatrix}. \tag{1}$$

Hence, the matrix **Y** can be given by:

$$\boldsymbol{Y} = \begin{bmatrix} \boldsymbol{y}_1 \\ \vdots \\ \boldsymbol{y}_m \end{bmatrix} = \begin{bmatrix} \boldsymbol{p}_1 \bullet \boldsymbol{X} \\ \vdots \\ \boldsymbol{p}_m \bullet \boldsymbol{X} \end{bmatrix}, \tag{2}$$

where matrix $\boldsymbol{Y} = [\boldsymbol{y}_1 \quad \cdots \quad \boldsymbol{y}_m]^T$ contains the principal components and each vector $\boldsymbol{P} = [\boldsymbol{p}_1 \quad \cdots \quad \boldsymbol{p}_m]^T$ denotes the eigenvector of the covariance matrix $\boldsymbol{S}_x$, which is defined as follows:

$$\boldsymbol{S}_x = \frac{1}{n-1}\boldsymbol{X}\boldsymbol{X}^T. \tag{3}$$

Y acts as the rotation and stretch of **X**, and its components have the largest variance to explain the information contained in **X** to the greatest extent.[1]

3.2. The time-varying Granger causality test

The intricate financial environment urgently needs cutting-edge model systems to accurately characterize the relationship between variables. However, the traditional Granger test based on the time-invariant model cannot track the dynamic behavior between financial series, making it difficult to achieve a new leap in the field of econometric analysis, especially across the time dimension. Time-varying relationships allow real-time monitoring of market ups and downs, which has been unanimously recognized by scholars (Diebold and Yilmaz, 2014). In addition, research by Shi et al. (2018) has repeatedly emphasized the sensitivity and vulnerability of causality to the sample period. The superposition of the above factors inspires us to explore the complicated relationship between the digital economy and the financial market through the time-varying Granger technique.

The time-varying Granger method developed by Shi et al. (2018, 2020) omits the detrending step and aids in endogenous detection of the causation switch-on and switch-off dates. The method provides three tests to explain causality, including forward expanding (Thoma, 1994), rolling window (Swanson, 1998) and recursive evolving (Phillips et al., 2015). In the existing literature, the forward window is the least favored, while the latter two provide more reliable estimation results (Raggad, 2021). Moreover, it is worth noting that Granger tests based on VAR or ECM frameworks suffer from cumbersome non-standard limit theories and parameter dependencies, which inevitably lead to scale distortion (Toda and Phillips, 1994). To overcome this deficiency, the lag-augmented VAR (LA-VAR) method is regarded as a well-deserved alternative procedure due to its superiority in scale control and dimensional stability (Toda and Yamamoto, 1995), and a modified Wald (MWald) statistical method is derived from it.

Suppose the time series $\{y_t\}$ can be derived by the following process:

$$y_t = \alpha_0 + \alpha_1 t + \mu_t, \tag{4}$$

[1] For more derivation details and method principles, see Shlens (2003).

where μ_t follows the VAR(p) specification:

$$\mu_t = \beta_1 \mu_{t-1} + \cdots + \beta_p \mu_{t-p} + \varepsilon_t, \tag{5}$$

with ε_t denotes the error term. If substituting Eq. (5) into Eq. (4), we can get:

$$y_t = \gamma_0 + \gamma_1 t + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + \varepsilon_t, \tag{6}$$

where γ_i denotes the function of α_i and β_j with $i = 0{,}1$ and $j = 1 \ldots$, p.

The LA-VAR model proposed by Dolado and Lütkepohl (1996) and Toda and Yamamoto (1995) advocates to construct a Granger causality test for the possibly integrated variable y_t:

$$Y = \tau\Gamma' + X\Theta' + B\Psi' + \varepsilon, \tag{7}$$

where $= (y_1, \cdots, y_T)'_{T\times n}$, $\tau = (\tau_1, \cdots, \tau_T)'_{T\times 2}$, $\tau_t = (1, t)'_{2\times 1}$, $\Gamma = (\gamma_0, \gamma_1)_{n\times 2}$, $X = (x_1, \cdots, x_T)'_{T\times np,}$ $\Theta = (\beta_1, \cdots, \beta_q)_{n\times np}$, $B = (b_1, \cdots, b_T)'_{T\times nd}$, $b_t = (y'_{t-p-1}, \cdots, y'_{t-p-d})'_{nd\times 1}$, $\Psi = (\beta_{p+1}, \cdots, \beta_{p+d})_{n\times nd}$, and $\varepsilon = (\varepsilon_1, \cdots, \varepsilon_T)'_{T\times n}$, with d denotes the maximum order of integration in y_t.

The null hypothesis of Granger non-causality is given by the following restrictions:

$$H_0 : \boldsymbol{R}\theta = 0, \tag{8}$$

where the parameter θ can be obtained by $\theta = vec(\Theta)$. $\boldsymbol{R}$ represents the $m \times n^2p$ matrix, where m is the number of restrictions. The last d-order lag vector of the coefficient matrix Ψ can be ignored because all elements are 0. $\widehat{\Theta}$ is the OLS estimator and can be defined as:

$$\widehat{\Theta} = Y'QX(X'QX)^{-1}, \tag{9}$$

where $Q = Q_\tau - Q_\tau B(B'Q_\tau B)^{-1}B'Q_\tau$ and $Q_\tau = I_T - \tau(\tau'\tau)^{-1}\tau'$. Let $\widehat{\theta} = vec(\widehat{\Theta})$ and $\widehat{\Omega}_\varepsilon = \frac{1}{T}\widehat{\varepsilon}'\widehat{\varepsilon}$, then the standard Wald test statistic of the null hypothesis can be expressed in the following form:

$$W = (R\widehat{\theta})'\left[\boldsymbol{R}\left\{\widehat{\Omega}_\varepsilon \otimes (X'QX)^{-1}\right\}\boldsymbol{R}'\right]^{-1}\boldsymbol{R}\widehat{\theta}, \tag{10}$$

in the above formula, the Wald test statistic asymptotically follows the χ^2_m distribution with m constraints.

Let f_0 denote the minimum number of windows required for estimation, f_1 the origination point of the regression, and f_2 the termination point of the regression. Then the Wald statistic over $[f_1, f_2]$ with a sample size fraction of $f_w = f_2 - f_1 \geq f_0$ is represented by $W_{f_2}(f_1)$ in the recursive evolving approach. The supremum (sup) Wald statistics can be written as:

$$SW_f(f_0) = \sup_{(f_1, f_2) \in \Pi_0, f_2 = f} \left\{W_{f_2}(f_1)\right\}, \tag{11}$$

where $\Pi_0 = \{(f_1, f_2) : 0 < f_0 + f_1 \leq f_2 \leq 1, f_0 \in (0,1) \; and \; 0 \leq f_1 \leq 1 - f_0\}$ indicates the minimum number of observations required to estimate the VAR model. Further, the additional flexibility gained by relaxing f_1 allows the process to find the optimal beginning point for the regression for each observation.

We use $\widehat{f}_e$ and $\widehat{f}_f$ to denote the starting and ending points of causality, respectively, which are defined by the first observation whose test statistic exceeds or falls below the critical value. Concretely, the abovementioned three algorithm require the statistic sequences to be as follows:

$$\text{Forward} : \widehat{f}_e = \inf_{f \in [f_0, 1]} \{f : W_f(0) > cv\} \; and \; \widehat{f}_f = \inf_{f \in [\widehat{f}_e, 1]} \{f : W_f(0) < cv\}, \tag{12}$$

$$\text{Rolling} : \widehat{f}_e = \inf_{f \in [f_0, 1]} \{f : W_f(f - f_0) > cv\} \; and \; \widehat{f}_f = \inf_{f \in [\widehat{f}_e, 1]} \{f : W_f(f - f_0) < cv\}, \tag{13}$$

$$\text{Recursive} : \widehat{f}_e = \inf_{f \in [f_0, 1]} \{f : SW_f(f_0) > scv\} \; and \; \widehat{f}_f = \inf_{f \in [\widehat{f}_e, 1]} \{f : SW_f(f - f_0) < scv\}, \tag{14}$$

where cv corresponds to the critical value of W_f and scv corresponds to the critical value of SW_f.

4. Data and description

4.1. Index construction: digital economy

Systematic measurement of the attention of the digital economy is a prerequisite for building a quantitative model. Irrational phenomena such as information hype flooded in the financial market make investors prone to social group rational deviation. Investor attention can further amplify the role of investor sentiment and heterogeneous beliefs, which will lead to abnormal changes in financial market prices (Hamid and Heiden, 2015). Since the Baidu Index can describe the attention of investors based on the data of netizens' search behavior on Baidu engine, this paper uses the Baidu Index as a proxy variable and uses the PCA method to construct the digital economy attention index.

The keywords of academic papers are the condensed and generalized themes of the papers, which can keenly reflect the research hotspots and are crucial for capturing the frontiers of scientific research in this field. Therefore, we first extract high-frequency and high-centric keywords related to the digital economy via the CtieSpace software,[2] then crawl the corresponding Baidu index through Python, and standardize the raw data. The processed data passed the KMO test and Bartlett's sphericity test, indicating suitability for subsequent factor analysis.[3] The PCA analysis results are shown in Table 1. According to the principle that the cumulative variance contribution rate exceeds 80% and referring to the scree plot (Fig. 1), we select the first four principal components to construct a comprehensive index of digital economy attention.

Fig. 2 depicts the trend of netizens' attention to the digital economy. The larger the composite index of digital economy attention constructed according to the PCA method, the higher the people's sentiment towards the digital economy, and vice versa. The curve shows a strong volatility characteristic of sudden rises and falls, from which we can draw two intuitive conclusions: First, the degree of attention based on online search is capricious, and market participants will overreact driven by their own subjective judgments. Second, the cyclical performance of netizens' attention indirectly reflects the alternation of high fever and downturn in the development of the digital economy.

4.2. Data source and descriptive analysis

To investigate the time-varying causality of the digital economy attention on financial markets, we develop our dissertation by using the Shanghai Composite Index (SSEC) and seven sector indices of technology, finance, consumption, medicine, commodity, industry, and telecommunication. All closing prices are retrieved from the WIND database. Considering the availability of data, our sample time interval from December 4, 2017 to July 8, 2022, with 1116 observations. As mentioned above, the time-varying Granger technique is robust to both integrated and cointegrated time series, and does not require detrending or differencing preprocessing, so this paper only takes the logarithm of the original closing price.

Table 2 presents the summary statistics for each incorporated data series. The most striking result to emerge from the data is the high-risk and high yield of the consumption sector, because it has the largest average return and standard deviation. Conversely, the performance of the commodity sector appears to be lackluster from an earnings perspective. Moreover, the results of skewness and kurtosis confirm that the price series of each sector deviates from the normal distribution. Fig. 3 further visualizes the evolution pattern of the price series over the sample period.

The plots show that the consumption industry benefits from the release of deferred demand in 2021, the stock price has been soaring. In addition, except for the finance and telecommunication industries, which are characterized by cyclical fluctuations, the prices of other industries have a clear upward trend in 2020–2021. We can also find that the overall market and various sub-sectors show a downward and volatile trend in 2022, which is attributed to the Russian-Ukrainian conflict, the Fed's tightening monetary policy, and the risk of funds' “group” investment.

5. Empirical findings and discussion

This section is made up of two parts. Prior to undertaking the investigation, we first execute two typical unit root tests on the variables involved in our study. In parallel, from a unique perspective of time-varying dynamics, we delve into the precise episodes of causality between digital economic attention and financial markets. Through this, we provide a comprehensive interpretation of how digital transformation is deeply integrated into the financial market and injects new momentum into all walks of life.

5.1. Unit root test

Although the time-varying Granger framework omits the step of pre-filtering variables by taking differences, knowing the order of integration of the model is an indispensable prerequisite. Therefore, the paper conducts Augmented Dickey-Fuller (Cheung and Lai, 1995) and Phillips-Perron (Phillips and Perron, 1988) tests with a linear trend as an exogenous variable and reports the results in Table 3. Figs. 2 and 3 give an initial impression that at least all financial time series are non-stationary while the digital economy

[2] The extracted keywords are listed as follows: digital economy, digitization, real economy, manufacturing, smart manufacturing, inclusive finance, innovation, smart city, factors of production, e-commerce, sharing economy, cross-border e-commerce, digital publishing.

[3] The KMO test value is 0.855, and the P value of Bartlett's sphericity test is significant at the 1% level.

Table 1
Variance decomposition principal component extraction analysis.

Principal component	Eigenvalues	variance contribution rate(%)	Cumulative variance contribution rate(%)
1	5.5952	43.04	43.04
2	2.4857	19.12	62.16
3	2.0175	15.52	77.68
4	0.6478	4.980	82.66
5	0.4197	3.230	85.89
6	0.3601	2.770	88.66
7	0.3430	2.640	91.30
8	0.2933	1.750	93.56

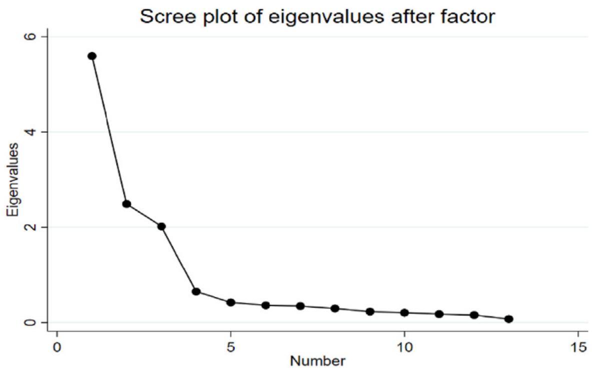


Fig. 1. Scree plot of eigenvalues.

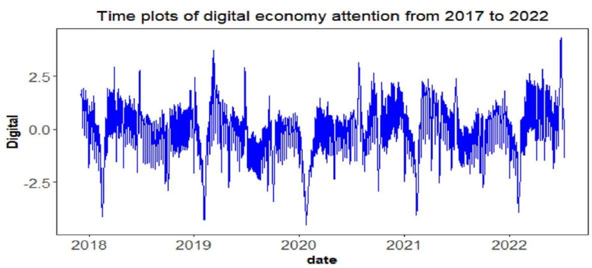


Fig. 2. Change trend of digital economy attention during period from December 4, 2017 to July 8, 2022.

Table 2
Descriptive statistics of price series.

	Min	Max	Mean	Stdev	Kurtosis	Skewness
SSEC	7.810	8.220	8.051	0.101	2.039	−0.312
Technology	7.735	8.708	8.249	0.217	2.159	−0.347
Finance	8.349	8.707	8.532	0.081	2.075	−0.285
Consumption	8.791	10.027	9.425	0.325	1.595	−0.000
Medicine	8.485	9.360	8.938	0.207	1.962	0.090
Commodity	7.209	8.187	7.568	0.242	2.093	0.578
Industry	7.452	8.069	7.741	0.156	1.817	0.276
Telecom	7.713	8.272	7.992	0.105	2.512	−0.034

Note: (i) The sample uses daily data. The sample period of price series is from December 4, 2017 to July 8, 2022. (ii) * denotes the 10% significance level; ** denotes the 5% significance level; *** denotes the 1% significance level.

attention is stable. The unit root test further confirms our conjecture that prices are stable at their respective first-order differences, and digital economic indicator is stationary at its level, indicating that the maximum order of integration is I(1). In addition, we imitate the practice of Shi et al. (2020), the lag length is selected according to the criterion of minimizing AIC, and the critical value of the Wald statistic corresponding to the three algorithms is obtained by 1000 repetitions of the residual bootstrap process. Finally, we implement a heteroskedastic consistent version as shown by Madaleno et al. (2022).

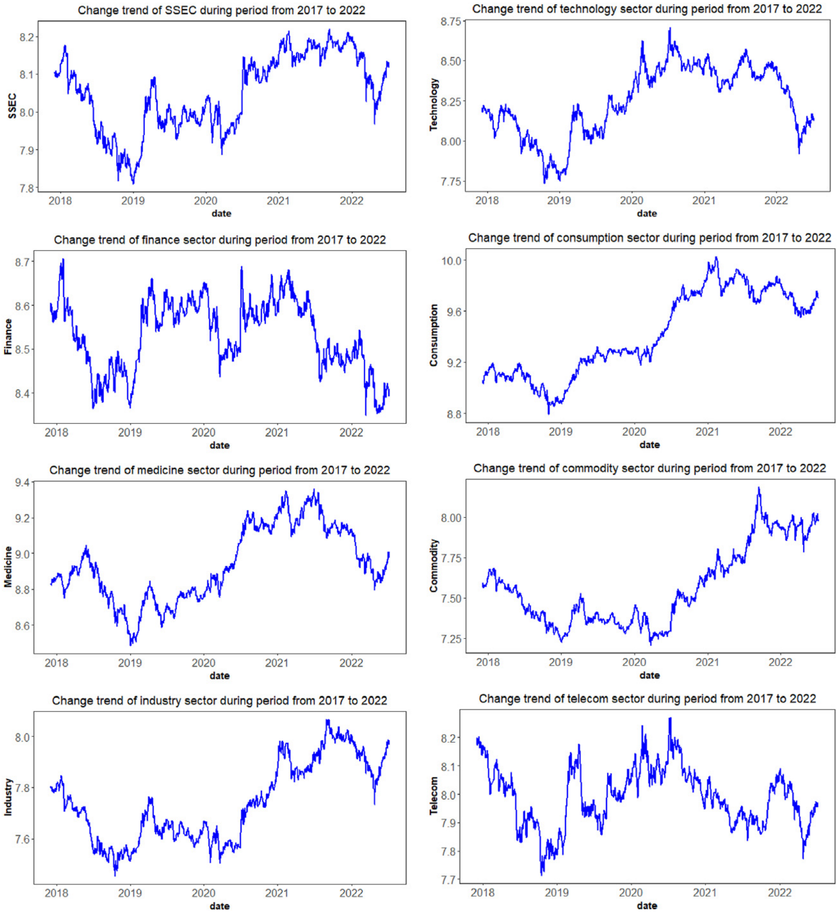


Fig. 3. Change trend of SSEC and all sectors during period from December 4, 2017 to July 8, 2022.

Table 3
Results from unit root tests.

	Levels		First-differences		Outcome
	ADF	PP	ADF	PP	
SSEC	−2.757	−2.762	−23.183***	−33.353***	I(1)
Technology	−1.609	−1.632	−22.609***	−32.863***	I(1)
Finance	−2.654	−2.640	−23.185***	−33.514***	I(1)
Consumption	−1.593	−1.612	−23.448***	−33.391***	I(1)
Medicine	−1.643	−1.637	−23.861***	−32.883***	I(1)
Commodity	−2.050	−2.090	−22.508***	−32.330***	I(1)
Industry	−2.699	−2.666	−23.637***	−33.466***	I(1)
Telecom	−3.162*	−3.211*	−22.643***	−32.794***	I(1)
Digital	−7.781***	−8.689***	/	/	I(0)

Note: (i) The augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test report unit root test results with the null hypothesis of non-stationarity. (ii) * denotes the 10% significance level; ** denotes the 5% significance level; *** denotes the 1% significance level.

5.2. Granger causality between the digital economy and financial markets

With the recent favorable policies in the field of the digital economy, digital transformation is entering a rapid development track, which is expected to become a forward-looking guide for investment in the stock market. Netizens' attention based on public opinion data, as a carrier of information dissemination that cannot be ignored, is bound to create ripples in the financial market (Li et al., 2021). Considering the above two points, this paper pioneers to explore the time-varying causal spillover relationships between the digital economy attention and the financial market, in order to comprehensively reveal the penetration and the omni-directionality of the digital economy revolution.

Table 4 reports the robust Wald test statistics for Granger causality based on the forward, rolling, and recursive algorithms with the

Table 4
Wald tests of Granger causality.

Causality	Forward			Rolling			Recursive		
	Wald	95th	99th	Wald	95th	99th	Wald	95th	99th
$digital \xrightarrow{GC} SSEC$	16.116***	9.106	13.927	25.277***	9.430	11.726	25.290***	9.679	13.927
$digital \xrightarrow{GC} technology$	6.269	12.789	17.907	17.517*** ***	12.699	17.825	18.249*** ***	12.841	18.884
$digital \xrightarrow{GC} finance$	12.553**	9.607	16.344	14.329**	9.890	15.323	20.752*** ***	10.070	16.344
$digital \xrightarrow{GC} consumption$	18.923***	9.583	13.320	20.629***	9.467	14.253	23.717*** ***	9.879	14.363
$digital \xrightarrow{GC} medicine$	11.378**	9.117	16.527	18.364***	9.625	16.016	19.662*** ***	9.625	16.527
$digital \xrightarrow{GC} commodiy$	11.747**	9.952	14.077	27.352***	10.341	16.258	28.105*** ***	11.165	16.258
$digital \xrightarrow{GC} industry$	15.839***	9.714	16.481	20.380***	9.970	16.246	25.241*** ***	10.236	16.481
$digital \xrightarrow{GC} telecom$	6.429	11.748	17.705	13.890**	12.266	17.453	21.809*** ***	12.282	17.705

Note: (i) The table reports the robust Wald test statistics of Granger causality and the 95th and 99th quantiles of the empirical distributions of the bootstrap statistics. (ii) * denotes the 10% significance level; ** denotes the 5% significance level; *** denotes the 1% significance level.

95th and 99th quantiles of the empirical distributions of the corresponding bootstrap statistics. From the results in the table, it can be clearly found that the detection success rate of the recursive algorithm is the highest, followed by the rolling window, and the detection performance of the forward window is much lower than the former two. Therefore, in the subsequent analysis, we only present the time-varying Granger causality diagram under rolling and recursive windows.

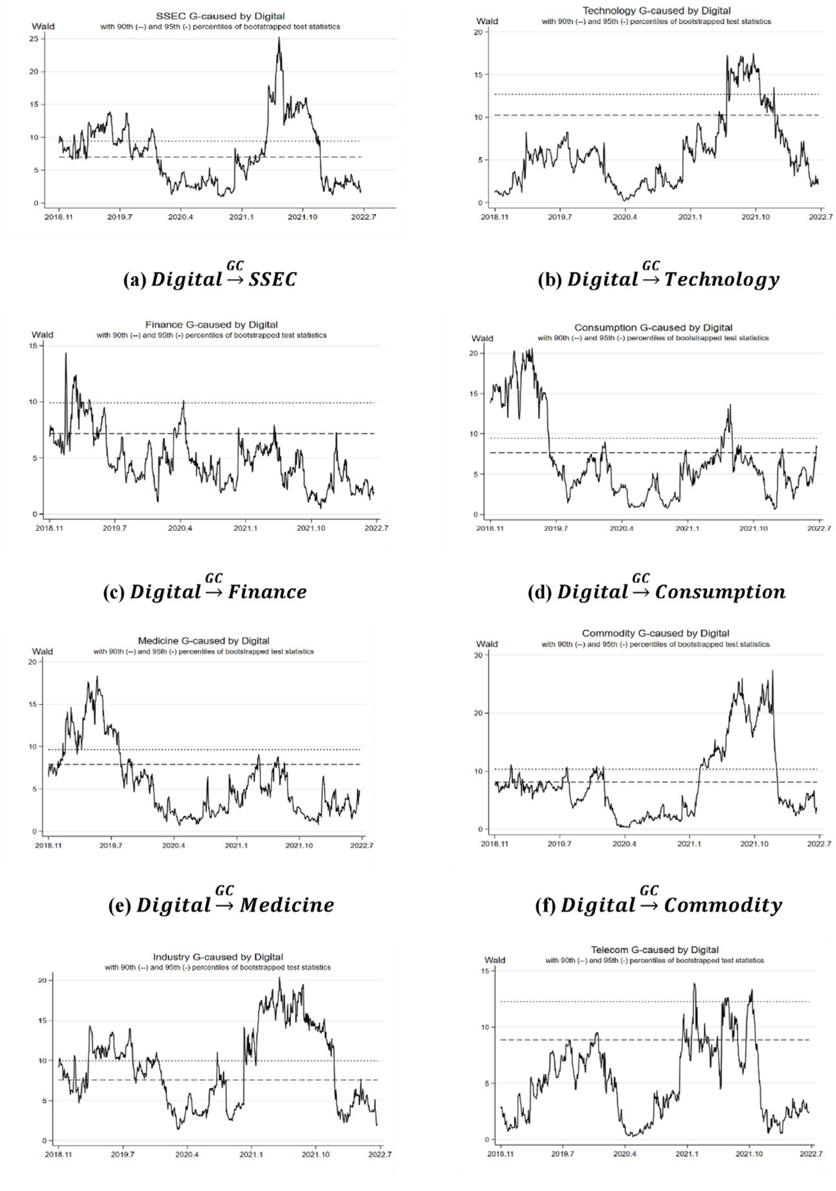
In addition, we can also have a preliminary impression of the degree to which the digital economy attention has spread to the financial market and various sub-sectors: China's stock market, consumption, and industry sectors are sensitive to the digital economy and are effective recipients of its attention. In contrast, the finance, pharmaceuticals, and commodity sectors are moderately influenced by the digital economy attention, while the telecom and technology sectors appeared to be less affected by the contagion of investor sentiment towards the digital economy. How the digital economy attention spills over to the financial market at different time points and what is the root cause behind these phenomena will be discussed further in the following visualization analysis.

Figs. 4 and 5 depict the Granger results based on rolling and recursive algorithms, respectively. When the curve exceeds a critical level at a certain period, significant causal relationships are discovered. Starting from the causal impact of the digital economy attention on the Shanghai Composite Index (Figs. 4a and 5a), two obvious causal relationships are detected in the early and late stages of the sample, and the causal spillover displayed by the recursive window is more persistent. Wei and Chen (2015) demonstrated that the Chinese stock market has the distinctive characteristics of a large group of retail investors and prominent information asymmetry, so the limited attention of investors can easily lead to anomalies in the financial market and skyrocketing and falling stock prices. Coupled with China's beginning to explore economic issues from a digital perspective, the digital economy is gradually heating up. Therefore, the rise of the digital economy will be infinitely magnified in the network attention and further radiate to the macro market. Meanwhile, considering the profound potential of digital elements and the intangible value created for enterprises (Spence, 2021), this trend of transition to a digital economy will help the growth rate of China's stock market to take the lead in the region.

An unexpected finding that causality disappeared during the COVID-19 pandemic may be related to the heterogeneity of investor attention on the stock market (Chen et al., 2013). In other words, market participants were in low spirits during the pandemic. They were less active in the market due to loss aversion, coupled with the difficulty of relying on the digital economy to deal with the downward pressure on the economy, so the degree of correlation between the digital economy attention and Shanghai Composite Index has declined. After entering 2021, the causal relationship is significant again. This is because China's development focus has gradually shifted from focusing on land, manpower, and machines to the level of digital technology and digital development under the normalized epidemic situation. It has shown a pattern dominated by digital space, thus becoming a key boost to the recovery of the financial market. In addition, with the effective control of the domestic epidemic and the orderly resumption of work and production, the economic situation has gradually improved, and the recovery has gained momentum, which is unique worldwide. Against this backdrop, confidence in the financial markets was effectively boosted, with market attention and investor sentiment picking up.

The Shanghai Composite Index reflects more on the operation of the national macro-financial market. Next, we will further analyze whether listed companies in different industries will be affected by the digital economy attention from a micro-enterprise perspective. Regarding the causality from digital economy attention to the technology industry, the results of the forward algorithm reveal that significant causality only exists in mid-to-late 2021. The results of the recursive algorithm suggest that this significant causality extends to early 2022 (Figs. 4b and 5b), which shows that the spillover of the digital economy attention to the technology industry is short-lived in the time dimension. As the mainstay of expanding domestic demand and driving the digital transformation of industries, information technology has broadened the investment prospects of the financial market. The deep integration of emerging technologies such as the Internet of Things, cloud computing, blockchain, and artificial intelligence with the digital economy has become an accelerator for its rapid startup (Liu et al., 2021). It is shown that the technology industry, known as the “digital engine”, has an inseparable relationship with the digital economy.

Despite their promising development prospects, these tech assets are highly susceptible to financial risk contagion, especially for investor attention or sentiment assessments (Adekoya et al., 2022). Therefore, when investors pay more attention to the digital economy, under the influence of subjective investment decisions, the probability of technology stocks being selected as investment targets surges, resulting in causal spillovers. In addition, in the economic recovery and reconstruction in the post-epidemic period, the



(a) $Digital \overset{GC}{\rightarrow} SSEC$
(b) $Digital \overset{GC}{\rightarrow} Technology$
(c) $Digital \overset{GC}{\rightarrow} Finance$
(d) $Digital \overset{GC}{\rightarrow} Consumption$
(e) $Digital \overset{GC}{\rightarrow} Medicine$
(f) $Digital \overset{GC}{\rightarrow} Commodity$
(g) $Digital \overset{GC}{\rightarrow} Industry$
(h) $Digital \overset{GC}{\rightarrow} Telecom$

Fig. 4. Time-varying Granger causality with heteroskedastic-robust specification: Rolling window.

high-tech industry has shown relatively strong resilience and driving force, and the cumulative year-on-year growth rate of industry investment is the first to turn from negative to positive, which explains why causality is significantly detected after 2021. As for why causality is invalid most of the time, a plausible explanation is that in the context of digitalization, technology assets often play the role of recipients as the possible cyber risks and security threats of modern technology can harm the performance of the companies involved and attract the investors' attention (Adekoya et al., 2022).

Fig. 4c shows a significant causality from digital economy attention to financial sector in the first half of 2019, while a longer period of significant causality emerges under the recursive algorithm (Fig. 5c). The digital economy is giving birth to a new transformation in the modern financial format by changing the payment side, reconstructing the currency side, empowering the supply and demand side, and strengthening the supervision side. In particular, the banking industry, as the core of modern finance, has become the key to supporting the establishment of new advantages and competitiveness of China's digital economy (Niemand et al., 2021). In 2019, the People's Bank of China released the "FinTech Development Plan" which clearly takes technology empowerment as the basic principle. At the same time, the China Banking and Insurance Regulatory Commission issued the "Guiding Opinions on Promoting Supply Chain Finance to Serve the Real Economy", encouraging the use of digital technology to achieve the authenticity of supply chain finance

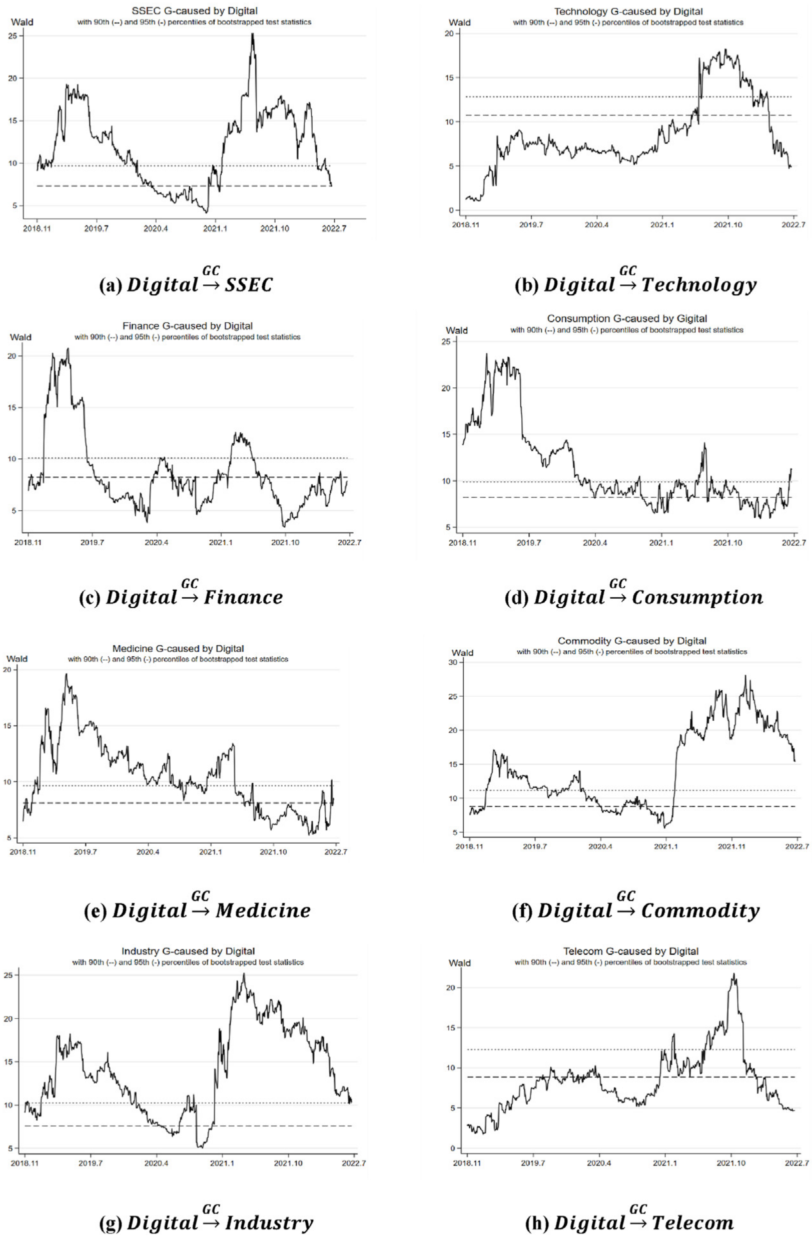


Fig. 5. Time-varying Granger causality with heteroskedastic-robust specification: Recursive evolving.

transactions and improve the bank's risk control level. In this scenario, netizens have a positive attitude towards the digital economy reshaping the financial structure, which is further reflected in the considerable financial sector prices.

However, although we believe that fintech-led digital means have a positive impact on the traditional financial industry, it has not yet fully controlled the financial market, which is consistent with the conclusion of Chen et al. (2022) that the financial industry often acts as the spiller of fintech information transmission rather than the receiver. Furthermore, from the perspective of investor attention, on the one hand, as the information disclosure mechanism in the domestic financial and securities market is not perfect, the "herding effect" is evident due to the blind following of individual investors, so the share price premium caused by investor attention quickly disappears. On the other hand, small and medium-sized investors are very passive in access to key information, such as the digital economy and lack subjective judgement, making it impossible for them to accurately digest financial market information, thus resulting in investors' inadequate response to information.

The causal spillover trends from digital economy attention to consumption and medical industries are similar, in which the coverage span of significant relationships under the forward window (Fig. 4d and e) is not as durable as the recursive window (Fig. 5d and e). The curves collectively reveal that people's attention to the digital economy will have a broad and profound impact on the consumption and pharmaceutical industries in 2019, and each has a short-lived significant peak in 2021. Medical care and consumption are closely related to people's lives, and they are willing to obtain relevant information from Internet channels, so public sentiment and online attention will be fully reflected in the price of the sector (Jiang et al., 2022). As we all know, 2019 is the “first year of 5G commercial use”, simultaneously, e-commerce live broadcasts have also begun to enter the public eye. Their popularization and application have not only given new momentum to economic growth and assisted the formation of a smart society, but also become a hot spot for consumers and investors, thereby driving the digital and intelligent development of traditional industries such as consumption and medicine. Furthermore, after the reshaping and baptism of the entire market by the COVID-19 epidemic, people's consumption concepts and lifestyles have undergone tremendous changes. The intelligent upgrading and digital exploration of the industry have become rigid needs, and online consumption and remote consultation based on digital technology will gradually become the norm and continue to inject strong vitality into the economic recovery.

The only difference between Fig. 5d and e is that a visibly huge and significant causality during the pandemic exists only in industries ranging from digital economy attention to medicine, with no clear evidence to support it in the consumption industry, which is attributed to the transformation and breakthrough of digital medical care under the raging epidemic. Although COVID-19 has shaken the global medical service system, China's medical system has demonstrated excellent resilience under the wave of digitalization, including intelligent consultation, Internet hospitals, pharmaceutical e-commerce, etc. With such widespread and large-scale attention, a more valuable digital health model is emerging and thriving. In contrast, the depressed mood of people during the sudden public health event has caused the online consumption platform to face a short period of stagnation, so the causal effect is not significant.

Considering the causality impact of digital economy attention on the commodity industry, extreme significance is more common at the end of the analysis period. Especially the results of recursive algorithms, showing higher evidence of causation, with significant causal effects in the first half of 2019, early 2020 and beyond into 2021 (Figs. 4f and 5f). At present, the extensive model of “relying on scale for profit” in the commodity industry has become unsustainable, and enterprises have entered a transition period of “intensive cultivation”. Relying on the digital economy to reshape the commodity supply chain has become an industry consensus (D'Ignazio and Giovannetti, 2014). Relevant practitioners further recognize that digital transformation can improve the quality and efficiency of commodities, reduce resource and energy consumption, and thus move towards the middle and high end of the global value chain. From this, the plausibility of the significant causality from the digital economy attention to the commodity sector is clarified.

Academics link search engine-based attention to investor demand for information, validated across commodities (Prange, 2021). Specifically, the global economic resonance slowed down in 2019, and the demand side effectively suppressed the overall commodity. The spread of COVID-19 in early 2020 has once again put the commodity supply chain under relatively heavy downward pressure (Guo et al., 2022). Under the above circumstances, commodities are in urgent need of digital transformation to improve the weak status quo of the industry. After 2021, the epidemic has entered a normalized operation track, coupled with the fluctuation of energy prices caused by the situation in Russia and Ukraine. Therefore, in order to help upstream and downstream enterprises resume work and production as soon as possible and gain momentum for sustainable development, accelerating the digital transformation of bulk industries is still a long-term solution.

Regarding the causal relationship between the digital economy attention and industry, empirical results generally show that there is a significant causality from the end of 2018–2019, and a larger magnitude and wider range of significant Granger relationships throughout 2021. The recursive results suggest that this significant causation will continue until 2022 (Figs. 4g and 5g). Based on the results of the Granger test report, we agree with Möller (2016) that enabling high-quality manufacturing to efficiently deliver products to the market can be achieved by bringing digitalization into the industrial whole industrial setting. There is also strong contextual evidence supporting causal spillovers between digital economy attention and industry. Specifically, since the concept of Industry 4.0 was proposed, the digital economy relying on advanced intelligent technology has brought disruptive changes to industry, especially manufacturing. The deep integration of data elements can change the technical structure of the industry and thus affect the production process (Yang et al., 2021).

Interestingly, the obvious Granger relationship disappeared during the COVID-19 pandemic. The possible explanation is that the sudden pneumonia virus caused the entire industrial chain to shut down, the prevention and control measures cut off the logistics of the production of enterprises, resulting in the serious problem of blocked labor flow. In such a sluggish market environment, the attention of netizens was distracted. However, the epidemic crisis has forced enterprises to digitize, and people have simultaneously realized the urgency of digital transformation of the industrial industry. Therefore, in the post-epidemic era, relying on digital power to realize intelligent manufacturing and digital production has once again become a hot spot of online public opinion.

Finally, we consider the causal link between the digital economy attention and telecom industry. Figs. 4h and 5h indicate that the apparent Granger relationship is generally limited and only exists for a small period in 2021. Extensive research acknowledges that telecommunications infrastructure and services play a central role in sustaining the functioning of the modern economy (Vu et al., 2020), and that telecommunications service operators, who build the bridges of basic communications, have become the vanguard of digital industrialization. Among them, the digital life scene that people can reach and perceive the deepest is fully infiltrating people's daily life with an unprecedented development momentum. Therefore, the attention of netizens in the digital economy will penetrate into the telecom field to a certain extent, especially after the special point in time when telecom companies actively implement their cloud-to-digital transformation strategies in 2021. As for the explanation that the Granger relationship from the digital economy attention to the price of the telecom industry is not significant in most cases, we believe that it should be based on the fact that the telecommunications industry is an oligopoly, making its price mainly subject to government regulation and market competition.

6. Conclusion and policy implications

Although the digital economy has been widely debated in academic circles and a large body of literature indicates that investor attention can explain financial anomalies and stock price volatility, some combined exploration is lacking. To address the gaps in previous literature, this paper, for the first time, extracts the Baidu index keywords through crawler technology and constructs the digital economy attention index based on the principal component analysis method. Meanwhile, we analyze the impact of digital economy concerns on financial markets from a micro-industry perspective through a time-varying Granger approach, after considering the time heterogeneities.

We summarize our main findings as follows: First, the degree of attention based on the online search is capricious and the cyclical performance of investors' attention indirectly reflects the alternation of high fever and downturn in the development of the digital economy. Second, the results of the Granger test show that digital economy attention has varying degrees of causal spillover on the overall stock market and stock prices across sectors, with time-varying characteristics. Specifically, digital economy attention has a broader time horizon for causal impacts on the SSEC, industry, consumption, medicine, and commodity sectors, while it has relatively less predictive power for financial, technology, and telecom sectors. Third, depressed market sentiment exacerbated by the outbreak of COVID-19 has led to a causal association from digital economy attention to financial markets, which is generally limited in 2020. However, a period of flattening investor sentiment in the wake of the pandemic, combined with the digital economy revitalizing financial markets and assisting the industry recovery, led to causality becoming significant again after 2021.

To summarize, the findings of this paper are both a beneficial supplement to behavioral finance theory and of profound practical value to investors, companies and government. Investors should be prudent in grasping market dynamics and reducing irrational behavior in investment decisions. Companies should closely track changes in investor sentiment while relying on data resources and digital technology to transform “data silos” into “data islands” to stand out in the post-epidemic era. For the government, on the one hand, it is necessary to release the digital development dividend. On the other hand, they can provide data support for preventing and resolving abnormal stock market volatility by dynamically monitoring and directing investors' attention in real-time. In addition, the post-epidemic sentiment premium of listed companies' share prices is greater than that before the epidemic, meaning that in the era of rapid digital development, regulators need to pay more attention to market volatility brought about by changes in public sentiment and public opinion.

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