Do Institutional Group Holding Anomalies Drive Broad Market Trends?
Based on Shannon Entropy in Network Systems

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ABSTRACT

This paper focuses on the behaviour of institutional investors in the Chinese stock market and quantifies their “group holding” behaviour. Using the Shannon entropy in network systems, the authors measure institutional investors’ stock holdings strategy and internal private information transmission. A time-varying parametric vector autoregressive model between institutional behaviour and secondary stock market trends in China is constructed. The time-varying nature of the variables, response functions, and linkage mechanisms are explored and studied. The results of the data suggest that institutional investors’ stock holdings and private information transmission have different mechanisms of influence on stock market trends. In terms of direction, they may diverge; in terms of size, institutional investors’ “real money” is more impactful than “gossip”; in addition, they are asymmetrical in their stage of development and heterogeneous in different market conditions.

KEYWORDS

INTRODUCTION

The current state and development of China’s A-share market is a topical economic issue that has attracted considerable interest and discussion. Particularly, China’s stock market has been experiencing turmoil since June 2015, with ‘thousands of shares down 10%’ on repeatedly occasions. The volatility of the stock market and related systemic financial risks have attracted the attention of the government and regulatory authorities. The government’s work report also emphasized the need to improve the investor’s structure and maintain capital market stability. Investors who neglect the importance of structure are prone to market volatility, which is not unique to the Chinese market. In terms of composition, the securities market is a multi-party gaming market (Lou et al., 2019). A long-short battle between retail investors and institutions erupted during early 2021 in the US-listed company ‘GameStop Corp.’, causing enormous swings in the share price. In this case, individual investors helped drive the price of the target stock upward through emotional and herd trading, imitating the scale and characteristics of institutional investors’ trading. They sought to subvert the traditional trading order on the Wall Street, and it generated worldwide concern from the outset. This shows
that the shareholdings of investors can have a significant impact on the financial markets (Sakaki et al., 2021; Wang & Wei, 2021). Eventually, individual investors’ group holdings will be difficult to maintain due to the selling pressure and the impact on the liquidity of the underlying shares. Institutional investors own a greater proportion of shares, and their behaviour warrants further study.

At present, it is common to discuss institutional group holdings, sectors as group strengths, and individual stocks as group themes. First, this study defines the group holdings of institutional investors. The term ‘group holding’ is an abbreviation for holding a group together for warmth. It occurs when market participants continuously add to their positions in certain sectors until they become relatively concentrated in certain sectors and do not adjust their investment strategies by shifting positions at will. Financial research often distinguishes between true and false herds. Therefore, is herding behaviour a genuine recognition of the value of individual listed company, or is it a speculative activity driven by arbitrage (Musciotto et al., 2018), or merely a warmth behaviour arising from a market downturn? This is a question that needs to be investigated further in this study. According to the data analysis and empirical perspective, grouping is a structural holding. For a comprehensive assessment of this structure and system, it is important not to neglect the interactions between institutions, as ‘professionals’ of the same market position, as well as their market preferences, investment strategies, and private information transmission (Pedersen, 2021). Data mining and analysis are increasingly used to answer social science questions (Li & Liu, 2020). With the development of complex network theory and its applications in recent years, some scholars have begun to use network systems to characterize such social relationships (Ellinas et al., 2018; Guo et al., 2021; Ozsoylev & Walden, 2011). Network complexity reflects the links between individuals, and the dissemination of information within the network reflects the ease with which information can be shared among individuals. This evolution of a structured group increases the disorder within the system, which can be measured in terms of entropy.

Figure 1. Basic logic: summary of study steps and methodology

As shown in Figure 1, may therefore lead to corresponding market outcomes split the measurement into two components and the response analyses we applied to the model.

To build a network system of investor holdings, we selected quarterly data from the first quarter of 2006 through 2021, with a total of 61 periods. Shannon entropy was used to measure institutional shareholding strategies and dissemination of private information. A vector autoregressive model
with time-varying parameters was used to investigate the dynamic relationship between institutional shareholding strategies, private information spread, and stock market trends:

First, from the perspective of the research hypothesis, this study classifies investors’ group holding aberration behaviour into two factors, namely, behavioural strategy and information transmission, based on the entropy within the network.

Second, from the perspective of empirical models, the TVP-SV-VAR model is used to empirically analyse the sources of shocks to trend volatility in the secondary market based on the structure of market participants.

Third, from the perspective of the content and results, the analysis is conducted in terms of timeliness, timeline, and representative points in time, seeking the dynamic decision-making mechanism between irrational noise trading and value investment in different market contexts.

According to our extensive literature review, we have not yet found any relevant literature that applies density entropy and structural entropy to the study of investor behaviour and information transmission in network systems. Therefore this study is unique in terms of methodology, analytical perspective, and conclusion.

LITERATURE REVIEW

Stock Market Stability Perspective

Hirshleifer and Teoh (2003) agree that institutional investors do not necessarily increase stock market volatility or contribute to its stability. Bohl and Brzeszczynski (2006) found that institutional investors have increased their shareholdings in the Polish stock market. Furthermore, Cao and Petrasek (2014) found that institutional investors’ holdings reduce the liquidity risk of stocks, whereas hedge funds’ holdings show greater sensitivity. According to Ajina (2015), institutional investors’ shareholdings, especially pension funds, have a positive impact on stock market liquidity. As herd behaviour is networked, the level of experts acting as herd leaders and the sensitivity of their followers may influence investors’ limited rational responses to market volatility (Wang & Wang, 2018). Perhaps the market risk and return on individual stocks should be positively correlated, and then equity markets would eventually become rationalized and value-driven enough for investors to engage in long-term investing strategies. Specifically, institutional investors, in a network of relationships, hold concentrated holdings in groups, enabling them to make a greater impact by remaining cooperative. Vocal governance can be achieved without bundling (Crane et al., 2019). According to Wen et al. (2021), institutional investors in China favour inverse trading strategies and are optimistic that institutions will be able to predict future stock returns.

In contrast, research suggests that institutional investors do not reduce stock market volatility, but exacerbate it. Sias and Ttman (2006) found that complex information structures in a market environment can lead to herding behaviour and complex information structures can blow up price bubbles. In the context of the stock market, changes in the level of shareholdings, or the act of increasing or decreasing positions, have the most direct and obvious impact on the stock market. According to Poon et al. (2013), institutional investors’ herding behaviour resulted in an increase in bid-ask spreads and liquidity risks during the 2008 financial crisis. Moreover, institutional investors are likely to vote against individual investors because of their conflicts of interest. Musciotto et al. (2018) verified the existence of investor clusters in the market by exploring the time evolution of investor networks characterized by similarities in trading patterns. In their study of the Chinese stock market, Fan and Fu (2020) found that institutional investors have a negative influence. Additionally, institutional shareholding can further exacerbate the subsequent reactions to disappointing corporate news by increase selling pressure. This is further exacerbated by industry competition among institutional investors. Sakaki et al. (2021) argued that long-term institutional investors are associated with low mispricing of investee firms, and high institutional ownership leads to high stability of institutional investors’ equity. Meanwhile, short-term investors are argued to be under greater selling pressure.
(Fan & Fu, 2020), which does not seem contradictory. However, Wang & Wei (2021) argued that increased long-term institutional ownership had altered the channel of trading activity, resulting in low-frequency trading. The increase in short-term ownership encourages competition from other investors, reduces transaction costs, and improves stock liquidity.

**Private Information and Communication Perspective**

Depending on the private information and their different abilities to process new information, different investors have varying sensitivities when faced with a lack of public information on the market. Foreign and portfolio investors have an information advantage over direct investors (Kingsley & Graham, 2017). They have a greater influence on the equilibrium of stocks than other traders because of their dominant market position and sentiments. For example, private meetings are a typical form of sharing private information among investors. According to Bushee et al. (2018), investors’ private meetings are associated with stock anomalies and changes in institutional ownership. Trading returns were especially positive among firms with private meetings that provided complex information. Participating investors possess an informational advantage over non-participating investors. The participants are typically investors who regain a dominant position. Further, institutional investors’ access to information is more closely related to performance than retail investors. Drake et al., 2020 suggested that sophisticated and established institutions have an information advantage in determining their holding strategies.

Clearly, institutional investors have a greater advantage in terms of information than retail investors. Specifically, Lou et al. (2019) argued that individual investors and institutions have a tug-of-war between long and short, based on overnight news and that the behavioural strategies and information perceptions of the two are different, but they do not provide a reason for such anomalies. Akbas et al. (2021) suggested that this behavioural strategy and information perception anomaly stem from the battle between noise traders and arbitrageurs. With the exception of retail investors, even institutional investors differ in their access to private information and information processing. Weng and Tsai (2018) excluded the possibility of public information leading to mispricing and argued that private information is present in foreign institutional trading, resulting in price changes. However, Funaoka & Nishimura (2019) argued that institutions, such as securities, are more likely to have access to private information and use it to profit from IPOs. The impact of private information may be manageable, if institutional investors establish a benchmark for themselves (Breugem & Buss, 2019). Further, this benchmark reduces the value of private information, affects information aggregation, and increases return volatility. Therefore, institutional investors with lower benchmarks appear to have greater information value than those with higher benchmarks. Despite these heterogeneous differences between institutions, they form an integral network of relationships (Ellinas et al., 2018), and information is transmitted and exchanged between them (Cohen et al., 2008; Ozsoylev & Walden, 2011). Furthermore, Pedersen (2021) found that institutional investors’ superior ability does not fully explain their excellent holding and selling, as their business relationships enable them to generate private information related to listed companies, thus creating room for manipulation of the underlying stocks.

According to Heitzman and Klasa (2020), informed investors immediately trade new private information. The efficiency of trading is influenced by several factors, including the number of private information holders and institutional ownership, as well as the risk of breaking the law, public information, and other factors. The impact of public information on institutional investors can be as large as that of financial or policy uncertainty or even cultural context (Doring et al., 2021), or as small as that of weather forecasts of the day (Jiang et al., 2021). Wang and Wei (2021) asserted that long-term institutional investors have a lesser impact on stock market liquidity when they have sufficient public information. In contrast, short-term institutional investors increase stock market liquidity. Access to private information, however, induces an adverse selection bias among long-term institutional investors. Kong et al. (2021) demonstrated that active institutional investors indicate a
more sophisticated information processor that can adjust their trading strategies and capture abnormal returns based on information, such as analysts’ buy-side pressure. Individual investors, however, are asymmetrically informed about potential conflicts of interest between analysts and institutions, and require protection offered by market regulations.

As a result, institutional investors’ behaviour may be clustered, holdings may exhibit a herding effect, and private information can be transmitted through network channels. Further research is needed to determine whether institutional strategies and information dissemination act as stabilizers, especially from the perspective of network behaviour between institutions and the information risk contagion therein.

**MECHANISM ANALYSIS AND HYPOTHESIS**

The Bounded Rational Theory (Simon, 1955) addresses the Expected Utility Theory (Von Neumann & Morgenstern, 1944), in which the ‘economic man’ behaves in a perfectly rational manner with the goal of finding an optimal solution. According to the BR theory, the decision-maker acts with bounded rationality, which is between rationality and irrationality, and the behavioural decision is a process of finding a satisfactory solution. While traditional finance considers that investors are fully rational and their trading process is not affected by psychological factors, behavioural finance considers that investors are partially rational and their trading process is subject to various cognitive and behavioural biases. Moreover, investors, both individual and institutional seek to judge the market and make decisions rationally, but traders’ judgments and decisions are influenced by various psychological factors, such as cognition, motivation, and emotions (Haritha & Rishad, 2020).

From a behavioural perspective, there is a theoretical basis for the existence of irrational trading by institutional investors. We base this conclusion not on axiomatic assumptions, but on the validity of financial behavioural science in the study of institutional investors’ group holdings as an object of research. We first examine their behaviour.

Black (1986) argued that noise can be traded as information and affects the liquid markets. Specifically, it can be divided into two categories, liquidity trading and uninformed trading. Since, liquidity traders are confident in the market, they are willing to trade risky assets. However, the uninformed traders do not have correct and truthful information, causing the price of the asset to deviate from its value. In the case of efficient market hypothesis (Fama, 1970), both the types of noise traders can reach equilibrium. Market information is incorporated into the price of capital, making the price reveal its value. This, however, would not be the ideal scenario. In contrast to the efficient market hypothesis, not all information in the capital market is publicly symmetrical; some information is public, while some is private (Wang & Wei, 2021). Among them, private information transmission is an incomplete type of information, and according to Simon, investors tend to process information and make decisions with limited rationality. Individual as well as institutional investors with high levels of expertise and information advantage may not have the same standards assumed by rational people, while cognitive biases, investor sentiments, idiosyncratic information transmission, etc., may cause collective behaviour (Fan & Fu, 2020). This study is not based on efficient markets or full disclosure of information, but on the existence of noise trading, the validation of incomplete information, and a secondary focus on the private information of institutional investors.

Based on the concerns outlined in the two descriptions above, the following hypotheses are proposed from both a behavioural and an information-transaction perspective, respectively:

First, given the special characteristics of the Chinese securities market, such as the concentration of shareholdings in listed companies and the relatively low proportion of institutional investments, unlike in mature Western markets, where they can actively participate in the management of companies (Crane et al., 2019), institutional investors in China often function through the exit channels. If there is a link between the interests of two market legal persons, institutional investors may relinquish their oversight advantage and instead ‘collude’ with management on hidden information (Pedersen,
Additionally, some institutions are more interested in short-term trading than value or strategic investment, and if there is a potential downside risk for a listed company, they may still choose to exit with a speculative trade. When there is co-ownership between institutional investors, the competitive market relationship between them weakens and they form an inward-rolling group, in which private, idiosyncratic information and sentiment are more fluid internally. Therefore, there is an accumulation of releases for optimistic and pessimistic markets, exhibiting similar behavioural strategies (Musciotto et al., 2018). Generally, individual investors believe that they possess extensive investment expertise and experience. Their bullishness about specific sectors and stocks often serves as a guide and model for other investors. This process may exacerbate market instability. Despite this, our focus is not on whether the institutional holdings are all value stocks or hype stocks with high expectations. Instead, we focus on the impact of this behaviour, which is attributed to market effects. Therefore, Hypothesis 1 is proposed.

H1: Institutional investors are not rational traders in terms of their behaviour, and their group-holding strategies can influence the stock market.

Second, a large amount of public information is being announced on the stock market, and third-party institutions as well as market supervisory authorities work to reduce the level of information asymmetry at the market level, between listed companies and investors, in order to protect the interests of small and medium-sized investors. Institutional investors are the major participants and intermediaries in the market. Individual investors believe that institutions have a greater access to private information (Drake et al., 2020; Kingsley & Graham, 2017). As a result, their behaviour is interconnected, placing them in the same network system. There are channels for transmitting information between them, and private information may be disseminated through these network connections to influence stocks or markets. According to Tian (2011), geographical distance plays an important role in attracting institutions to evaluate and invest in start-ups. For empirical evidence, he uses both the geographic location of the firm as well as the distance between the venture capitalist and the firm. Distance was used as a proxy for monitoring costs to control for information and the resulting selection bias. Accordingly, spatial proximity may affect the information gathering costs of the rating agency and the monitoring costs associated with identifying the accuracy of the information. Thus, this leads us to wonder what difference the proximity of distance makes in the information theory. What causes proximity to reduce monitoring costs? Since public information is undifferentiated for recipients in modern economic markets, it is likely that distance differences bring about differences in the availability of private information. Musciotto et al. (2018) used complex networks as a research tool for studying investor heterogeneity and employed network topology as well as clustering feature algorithms in their analysis. Accordingly, when we build a network system, the distance between the two nodes in the behavioural network is not negligible when propagating private information.

In order to measure the information exchange between individuals in a network system, we drew inspiration by Tian (2011), Musciotto et al. (2018), and Xie et al. (2019). Our rationale is that spatial proximity has an impact on the information gathering costs of rating agencies and on the monitoring costs of validating the accuracy of the information. In a networked system, if the channels are more accessible or disorganized, the more likely it is that private information will be disseminated, making it more contagious. Private information is not the same as public market news, and those who pay extensive attention to it are more likely to be noise traders (Akbas et al., 2021). Instead, a rational trader may focus extensively on market performance, investment value, and long-term benefits. When there are limited rational traders in the market, they may act in unison under the guidance of private information, causing market volatility. Therefore, Hypothesis 2 is proposed.

H2: Institutional investors may be noise traders or at least limit their rationality to a certain extent, and the spread of private information among them may also affect stock market trends.
Third, in empirical studies of financial markets, it is more common to consider the heterogeneity of bull and bear markets, considering the state of the stock market (Wu & Lee, 2015). There are bound to be differences in investor behaviour and psychology under different circumstances. The same shocks have different effects on market (Wang & Wei, 2021). Our analysis also refers to ‘bull’ and ‘bear’ markets. Our review of relevant research indicates two broad approaches to establish a demarcation between the two: comparing market returns with a pre-determined threshold in a timeline, with periods below that threshold being ‘bear markets’ and others being ‘bull markets’. A more holistic approach is that of Capocci et al. (2005), who use actual stock market trends and landmark events to classify them. Considering the current situation of the Chinese stock market, we adopted the second method. Based on the characteristics of China’s stock market, which is often characterized by short bull runs, long bear runs, and large single-day fluctuations associated with stock market crashes, we argue that institutional behavioural strategies and information transmission are likely to be inter-period, heterogeneous, and stage-specific as well. Therefore, Hypothesis 3 is proposed.

H3: In terms of the stage of development, the behaviour of institutional investors is asymmetrical and heterogeneous across market states.

As shown in Figure 2, first we use the time varying parameter-stochastic volatility analysis for a period division, which varies with each stage of the development process of the Chinese stock market. During this time division, the behaviour of institutional investors and information transmission were analysed. Second, institutional investor shareholding is a behaviour characteristic of the Chinese stock market. As it is a group holding, there is a fine line between rationality and bounded rationality. If the grouping is driven by capital value, then its appearance is simply a convergence of value assets based on independent analysis by individual investors. If the grouping is driven by noise, then the phenomenon is likely to be herd behaviour generated by ‘gossip’. The objective is not to distinguish between the two, but to examine the role that holding behaviour plays in the market and attribute outcomes accordingly. Third, because of the group holdings, institutional investors transmit information in the same network and the institution holds private information. Information differs from strategy in that it is communicative in nature. Despite the fact that individual investors also hold incomplete
information, the objective is not to distinguish between private and incomplete information, but to examine the role of information transmission in the phenomenon of group holdings in the market and attribute it to the results. The phenomenon of institutional group holding can be demonstrated by analysing the response functions described in Figure 1 over different periods and at different points in time.

Our research focuses on the phasing of institutional investors’ behaviour between 2006 and 2021 based on the TVP-SV-VAR model, the relationship between shareholding strategy, information transmission, and stock market under time-varying impulse responses, as well as the linkage effect between institutional investors’ strategy and information.

NETWORK SYSTEMS AND VARIABLE MEASURES

Networks are becoming increasingly important in scientific research, representing a broad range of holistic aspects of the real world. Individuals are interconnected and interact within complex systems, allowing network science an ideal tool for describing the structure of things.

The current application of entropy operations in networks is widespread and has considerable advantages. The term ‘entropy’ (Shannon & Weaver, 1950) covers many disciplines, such as thermodynamic entropy, information entropy, and statistical entropy. The higher the entropy number under the same conditions, the more complex the network is internally, the higher the number of possible events, and the greater the uncertainty. This study attempts to measure institutional behaviour by using the Shannon entropy. Hence, the network is constructed as follows.

Institutional data is sourced from CNINFO by crawling and parsing annual reports, mid-term reports, quarterly reports, and fund reports of enterprises, while removing the national team-related institutions and corporate holdings. The data were compiled into a matrix. According to the specific definition, a connection is established between two institutions, if they hold shares in the same listed company and their proportion exceeds 3% of the total market value of the shares outstanding, noted as 1. As we analyse holding boundaries, the term institutional group holdings refer to an investment strategy in which investors keep adding to certain shares until they have a relatively concentrated position and do not make changes at will. To find concentrated holdings, we search for the correct percentage of holdings upward. According to the relevant shareholding ratio of shareholders’ rights in the company law, we can consider these ratios as investment habits since they correspond to shareholder rights. Consider 1%, 3%, and 5%, with 3% being the limit to ensure a complete structure in a complex network, especially after the 2015 stock market crash; if 5% is used, then the network becomes too diluted and discrete. A large adjacency matrix $M_{n \times n}$ is established, where elements $X_{ij}$ of the matrix indicate the number of stocks jointly held by institutions, reflecting the degree of correlation between the two in terms of similarity of their holdings, and the network is undirected. When node $v_i$ is not connected to any other node, it will be an isolated point in the matrix, but not in the final network. The matrix is $M_{n \times n}$, while the network is $V \times V$. The elements $X_{ij}$ of the matrix are assigned the following values:

$$X_{n \times n}[i, j] = \begin{cases} \sum A, & \text{if } (v_i, v_j) \in E \\ A, & \text{if } (v_i, v_j) \notin E \end{cases}$$

(1)

where, the set of fixed points is $V = \{v_1, v_2, \ldots, v_n\}$ and the set of edges is $E = \{(v_i, v_j) \in V \times V\}$, so the network is $G(V, E)$.

Using the adjacency matrix, we have transformed the holdings into a complex network that facilitates the network measures presented below. However, entering an adjacency matrix does not
mean entering a complex network. This is primarily because, although certain institutions appear to hold shares together, they do not form a network. From the perspective of network transmission, the individual points that are not connected to other institutions are not considered a part of the connected network. As we want to study the behaviour of institutions holding together, we should exclude such isolated data. Therefore, we created line graphs of the number of points and edges (basic attributes) of the network to better show how much data is actually included from the matrix to the network. The details are shown in Figure 3.

Figure 3. Line graph of data on basic network attributes

In the graph, the left vertical axis represents the closing price of the SSE Composite Index, while the right vertical axis represents the number of points and edges. According to Figure 3, certain patterns are evident between the numerical characteristics of an institution’s holding network and the stock index.

Institutional Holding Strategy: Algorithm Entropy

Brissaud (2005) discussed how entropy in physics measures degrees of freedom. In the information domain, entropy within a system denotes countable information and is a disorder. In finance, entropy is often referred to as information entropy or probability entropy (Zhou et al., 2013). For instance, Xu et al. (2011) used hybrid entropy to measure the risk in asset portfolios. Using mean-semi-variance-entropy, Zhang et al. (2012) examined the selection of asset portfolios with transaction costs. Through the application of complex network techniques, researchers have identified the topological properties of financial networks (Tabak et al., 2010). A growing body of research seeks entropy measures in network structures to solve practical problems, with Shannon entropy revealing the complexity (Zhang et al., 2017) and structure of networks (Anand & Bianconi, 2009). In terms of network complexity, the more heterogeneous the network, the more complex it is. The degree provides the most important information about network interconnections, and degree-based entropy is a valuable statistical property of networks (Xiao et al., 2008). Since the elements of a complex network are interconnected and interact with each other, it is impossible to measure the size and complexity of a financial network merely based on the nodes, edges, and density coefficients of the network elements. The concept of entropy describes the overall state of the system.
Based on the concept of entropy, we describe network complexity from the perspective of network elements, specifically the distribution pattern of network nodes, such as node A or B in Figure 4. Generally, this type of method measures the probability of nodes appearing in the system to identify density, which is effectively equivalent to the density entropy of the network. Therefore, this study follows the definition of Shannon’s entropy, the different methods, and the content of the study to measure the complexity of institutional holding networks using the weighted degree sequence entropy.

According to the definition of the degree of a complex network, we can define the degree of this undirected weighted network $G (V, E)$ as:

$$d(v_i) = \left\{ v_j : (v_i, v_j) \in E \right\} \quad v_j = \sum_{j}^{N} A_{i,j} \times W_j$$  \hspace{1cm} (2)

In equation (2), $W_j$ denotes the row genus weight of that node in the network, derived from the point weights of the nodes in the network $G (V, E)$ constructed by equation (1). $d(v_i)$ denotes the degree of $v_i$. The weighted degree considers the weights of the points (all non-zero elements in the adjacency matrix) and is equivalent to the degree in a traditional (0, 1) network. All point weights form a sequence which is normalized to:

$$P(d_i) = p(d(v_i) = d_i) = \frac{\left\{ v_j \in V : d(v_j) = d_i \right\}}{N}$$  \hspace{1cm} (3)

In Equation (3), $N$ is the number of nodes, $P(d_i)$ is the probability distribution of $d_i$ for each node in the network $G (V, E)$. According to the definition of Shannon entropy, the Shannon entropy of the complexity of the network $G (V, E)$ can be calculated as follows:

$$H(d_i) = - \sum_{i=1}^{n} P(d_i) \log P(d_i)$$  \hspace{1cm} (4)

In Equation (4), $H(d_i)$ is the normalized degree sequence entropy of the network $G (V, E)$, which is a weighted degree sequence entropy. Take the natural logarithm. The larger the value, the greater is the density or complexity of the system. Combined with the contents of this study, it is evident that the greater the weighted degree series entropy, the greater the density entropy and the greater the complexity in a network linked by institutional investors’ common stock holdings.
In Equation (5), a larger $E_{IIhold}$ indicates that the institution has entered the market and acquired a similar stock. However, a smaller $E_{IIhold}$ indicates that the institution is no longer invested in a similar stock or has reduced its holdings to below 3%. Both the directions of action are holding strategies adopted by institutions in the context of group-holding behaviour.

**Information Transmission: Structure Entropy**

The K-order structural entropy used in calculating the complex structure of a network is derived from the spread of infectious diseases (Zhang et al., 2021). Although epidemiology does not lack quantitative models, this model is based on a topological analysis of the node edges of complex networks. Essentially, each organism is regarded as a node that can infect the population if it has the propagation capacity of step $k$. This method is considered to be significantly superior to other structural entropies because of its ability to reflect the communication characteristics of the network more accurately (Huang et al., 2019). The algorithm still highlights the importance of the nodes, but its borrowed edge also considers the propagation, and we applied the communication characteristics of this model to calculate the information transmission between individual nodes through the edges of the network connection. In addition to considering network measures from the perspective of elements, such as the nodes and edges of the network, network measures can also be interpreted from the perspective of structure and change, such as spectral entropy, transfer entropy, $k$-structure entropy, and other perspectives. This class of methods focuses more on the evolutionary process of the network; the $k$-structure entropy focuses on the total number of nodes reachable within $k$ steps, while the propagation process of private information is similar to that of a channel without spacing nodes, such as nodes C, D, and E in Figure 4. The propagation process of private information resembles a channel without spacing nodes. Therefore, this study follows the definition of Shannon entropy and uses $k$-structure entropy to measure the propagation of institutional private information.

According to the definition of a node in a network, the number of nodes in this undirected weighted network $G (V, E)$ is as follows:

$$N^k_{ij} = \sum_{j=v_i}^{n} W_{ij} \times l_{ij}, W_{ij} \leq k \& k \in \{0,1,\ldots,d\}$$

where, $l_{ij}$ denotes the length of the shortest path from node $v_i$ to $v_j$ in the network $G (V, E)$. Weight $W_{ij}$ denotes the value of $v_j$ node in the network, while $k$ is the order or step size. Equation (6) calculates the sum of the weights of the edges traversed by the shortest path, which is the $k$th adjacency value of node $v_i$. According to the definition of Shannon entropy, the Shannon entropy of the structural aspect of the network $G (V, E)$ can be obtained as:

$$H^k = -\sum_{i=1}^{n} \frac{N^k_{v_i}}{\sum_{j=1}^{n} N^k_{v_j}} \log \frac{N^k_{v_i}}{\sum_{j=1}^{n} N^k_{v_j}}$$

In physics, $K$ represents Boltzmann’s constant, and when entropy is widely used in information theory, the value of $k$ is assumed to be 1. When the concept of entropy is applied to structural measures of networks, it is generally assumed that $K$ is also 1 (Ellinas et al., 2018), thus $k = 1$ in equation (7). $H^1$ is the 1-structure entropy of the network $G (V, E)$ and represents the weights’ sum of the edges experienced within one unit of steps. Take the natural logarithm. A larger value indicates that the
greater the sum of the weights of the edges experienced within one unit, the greater the internal structural connectivity of the system. This can be used to measure the structural entropy of the total number of other nodes accessible by each point in the network. Considering with the findings of this study, it is evident that the higher the 1-structure entropy of a network linked by institutional investors, the more disorderly the system is internally, and the greater the number of channels for information transmission between institutions.

$$E_{IIinfo} = H^1$$  (8)

In Equation (8), entropy tends to be disordered in information theory, and a larger $E_{IIinfo}$ indicates a greater likelihood of inter-institutional information transmission.

**Validity Test**

As shown in subfigure A of Figure 5, we calculate the total proportion of outstanding A shares held by institutions (excluding corporate holdings) and compare it with the $E_{IIhold}$ data for the shareholding strategy. We find that the overall trend between the two is consistent, which is consistent with common economic sense.

As shown in subfigure B of Figure 5, we calculate $E_{Iiinfo}$ by setting $k = 1$. The time trends obtained when we make $k = 2$ and when $k = 3$ are not significantly different, indicating that the calculations on institutional information transmission are valid.

As shown in subfigure C of Figure 5, $E_{IIhold}$ and $E_{Iiinfo}$, as entropy of the same network system, have the same overall trend. Wherein $E_{Iiinfo}$ is more volatile than $E_{IIhold}$ and is more closely related to the market.

**Figure 5. Variable time series**
Data Sources

The main reasons for selecting 2006 as the starting point of this study are: the introduction of the ‘Good Guys Raise Their Hands’ system and the establishment of the first public offering fund in 2001; the selection of social security fund managers in 2002; the adoption of the Fund Law in 2003; and the establishment of bank-based fund companies in 2005. A bank-based fund company was established in 2005, gradually completing the construction of the institutional, legal, and participant elements of the fund market operation. The year 2006 was therefore chosen as the starting point for this study. We selected the Shanghai Stock Exchange Composite Index for our analysis of stock market trends. It was the first index to be published in China and is the core index for determining the fundamental movements of the secondary securities market in China. Since it is the most representative, its use as a proxy variable for the movements of the Chinese stock market is justified.

Our study utilizes data from Wind, CSMAR, and CNINFO. The data ranges from Q1 of 2006 to Q1 of 2021, a total of 61 periods. There has always been a seasonal pattern in the Chinese stock exchange market because of various macro and micro factors, such as the timing of government decision-making meetings, credit allocation and social finance volume, as well as the fund company assessment system. To eliminate the effect of seasonal trends, this study uses the Census X-12 method to adjust the variables seasonally.

Table 1 summarizes the main variables as follows:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Agent variables</th>
<th>Calculation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Institutional Shareholding strategies</td>
<td>Weighted degree sequence entropy</td>
<td>$E_{IIhold}$</td>
</tr>
<tr>
<td>Private Information transmission</td>
<td>1-structure entropy</td>
<td>$E_{IIinfo}$</td>
</tr>
<tr>
<td>Market trends</td>
<td>SSE Composite Index</td>
<td>SC_Index</td>
</tr>
</tbody>
</table>

Figure 5 shows a line graph of the above variables. The data in Table 1 are shown in Subfigure C of Figure 5. It is difficult to summarize the impact of entropy variables on market indices based on the time series of the variables by simply observing trends.

MODEL CONSTRUCTION AND CONDITION ANALYSIS

Model Construction

The time-varying parametric vector autoregressive model (TVP-SV-VAR) proposed by Primiceri (2005), in which the coefficients and the covariance matrix of a model can change continuously over time, can explain the non-linear relationships and time-varying characteristics between economic phenomena. Nakajima (2011) compared this model to the VAR model by using numerical methods for simulation. He argued that the TVP-SV-VAR model can improve the accuracy of the estimation and can also provide a better fit to the economic data at various points in time. First, we establish a basic SVAR model with S-order lags:

$$Ay_t = F_1 y_{t-1} + F_2 y_{t-2} + \ldots + F_s y_{t-s} + v_t, t = s + 1, \ldots, n$$ (9)

where, $y_t$ is a $k \times 1$-dimensional column vector of k endogenous variables for period $t$. $A, F_1, \ldots, F_s$ are $k \times k$-dimensional coefficient matrices. $s$ is the posterior order of the endogenous variables. $v_t$ is a
vector of random perturbation terms with a variance-covariance matrix $\Omega$, also known as structural shock. The random error vector $v_t$ is the innovation process and is the $k \times 1$-dimensional structured shock matrix, $v_t \sim N(0, \sigma_t^2), A_t$ and $\sigma_t$:

$$
\Sigma = \begin{bmatrix}
\sigma_1 & 0 & \cdots & 0 \\
0 & \ddots & \vdots & \vdots \\
\vdots & \ddots & \ddots & 0 \\
0 & \cdots & 0 & \sigma_k
\end{bmatrix}
$$

In the SVAR, the parameters to be estimated in the VAR are reduced by adding constraints, assuming that the coefficient matrix $A_t$ is a lower triangular matrix:

$$
A = \begin{bmatrix}
1 & 0 & \cdots & 0 \\
\alpha_{21} & \ddots & \vdots & \vdots \\
\vdots & \ddots & \ddots & 0 \\
\alpha_{k1} & \cdots & \alpha_{k,k+1} & 1
\end{bmatrix}
$$

Equation (9) reduces to:

$$
y_t = B_1 y_{t-1} + B_2 y_{t-2} + \ldots + B_s y_{t-s} + A_t^{-1} \sum \varepsilon_t
$$

In Equation (12), $B_i = A_t^{-1} F_i, \varepsilon_t - N(0, I_k), t = s + 1, \ldots, n$, the equation superimposes the coefficient matrix $B_i$ according to the row elements of the matrix. The model can be expressed as:

$$
y_t = X_t \beta + A_t^{-1} \sum \varepsilon_t
$$

In equation (13), $X_t = I_k \otimes (y_{t-1}, y_{t-2}, \ldots, y_{t-s}), \otimes$ is the Kronecker product. $t = s + 1, \ldots, n$. Assuming that $\beta, A$, and $\sum$ are all fixed in Equation (13), then relaxing this assumption to the effect that all the parameters to be estimated all obey a time-varying first-order stochastic wandering process yields the TVP-SV-VAR model as:

(Regression)

$$
y_t = X_t \beta + A_t^{-1} \sum \varepsilon_t
$$

(Estimating factor)

$$
\beta_{t+1} = \beta_t + \mu
$$

(Time-varying coefficients)
\[ \alpha_{t+1} = \alpha_t + \mu_{\alpha} \]  
(Stochastic volatility)  

\[ h_{t+1} = h_t + \mu_{h} \]  

In the above expression, \( y_t \) is the institutional shareholding strategy, private information transmission, and stock market trends. \( t = s + 1, \ldots, n_\beta \) and \( h_{s+1} = N (\mu_{s0}, \Sigma_{s0}) \) and \( h_{s+1} = N (\mu_{h0}, \Sigma_{h0}) \). Assuming that external shocks follow a joint normal distribution, their random wandering process is as follows:

\[
\begin{bmatrix}
\varepsilon_t \\
\mu_{\beta_t} \\
\mu_{\alpha_t} \\
\mu_{h_t}
\end{bmatrix} 
\sim N
\begin{bmatrix}
I & 0 & 0 & 0 \\
0 & \sum_{\beta} & 0 & 0 \\
0 & 0 & \sum_{\alpha} & 0 \\
0 & 0 & 0 & \sum_{h}
\end{bmatrix}
\begin{bmatrix}
0 \\
0 \\
0 \\
0
\end{bmatrix}
\]  
(18)

Following Nakajima, the parameters were estimated using a Markov Chain Monte Carlo (MCMC) estimation method. The basic logic of the model is to first initialise the parameters with a priori distributions, then to extract the posterior distributions using the MCMC method, to estimate the posterior conditional probabilities of the parameters, and finally to complete the analysis with a time-varying impulse response function. In this study, it is assumed that the prior distribution of parameters \( \beta, \alpha \), and \( h \) is normal and their means \( \mu_{\beta0} = \mu_{\alpha0} = \mu_{h0} = 0 \); the covariance matrix \( \Sigma_{\beta0} = \Sigma_{\alpha0} = \Sigma_{h0} = 10 \times I \), and the \( i \)-th element of the covariance matrix follow the Gamma distribution. It is assumed that \( \Sigma_{\beta}, \Sigma_{\alpha} \) and \( \Sigma_{h} \) are diagonal matrices and that the following priori conditions are satisfied: \( (\Sigma_{\beta})_{i}^{-2} \sim \text{Gamma}(20, 0.01) \); \( (\Sigma_{\alpha})_{i}^{-2} \sim \text{Gamma}(2, 0.01) \); and \( (\Sigma_{h})_{i}^{-2} \sim \text{Gamma}(2, 0.01) \) use the MCMC method for the sampling simulations.

**Condition Analysis**

The TVP-SV-VAR model applies the tests and settings required as follows:
Data Stability Test

Table 2. Unit root test

<table>
<thead>
<tr>
<th>Variables</th>
<th>Type</th>
<th>ADF test</th>
<th>Significance</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>C, T, K</td>
<td>T</td>
<td>P</td>
<td>1%</td>
</tr>
<tr>
<td>SC_Index</td>
<td>C,0,1</td>
<td>-3.4536</td>
<td>0.0541</td>
<td>-4.1213</td>
</tr>
<tr>
<td>E_Ihold</td>
<td>C,0,1</td>
<td>-3.6877</td>
<td>0.0310</td>
<td>-4.1213</td>
</tr>
<tr>
<td>E_Info</td>
<td>C,0,1</td>
<td>-3.9216</td>
<td>0.0171</td>
<td>-4.1213</td>
</tr>
<tr>
<td>SC_Index</td>
<td>C,0,2</td>
<td>-4.0726</td>
<td>0.0115</td>
<td>-4.1243</td>
</tr>
<tr>
<td>E_Ihold</td>
<td>C,0,2</td>
<td>-3.6512</td>
<td>0.0340</td>
<td>-4.1243</td>
</tr>
<tr>
<td>E_Info</td>
<td>C, T,2</td>
<td>-3.8053</td>
<td>0.0232</td>
<td>-4.1243</td>
</tr>
</tbody>
</table>

Note: C, T, K are the intercept term, time trend term, and lag term in the ADF test model, respectively.

Modelling analysis using time series may lead to pseudo-regression problems between multiple time series with trends because they are all indirectly correlated with time factors. To avoid estimation bias due to \( y \), to be performed on the original series. If a series that is not stationary, then it is called a non-stationary series. For example, in a random walk time series. The last three rows for lag length choice 2 of Table 2 results show that the ADF tests for all series reject the original hypothesis (presence of unit root) at the 1% level of significance, and that the series are all stationary at the same confidence level and do not need to be differenced.

Model Lag Period

As shown in Table 3, the optimal number of lags is determined by the information criterion, such as AIC, SIC, and HQIC, at the time of model application.

Table 3 Optimal lag period

<table>
<thead>
<tr>
<th>Lag</th>
<th>LogL</th>
<th>LR</th>
<th>FPE</th>
<th>AIC</th>
<th>SIC</th>
<th>HQIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>66.0094</td>
<td>NA</td>
<td>1.86e-05</td>
<td>-2.3777</td>
<td>-2.2662</td>
<td>-2.3348</td>
</tr>
<tr>
<td>1</td>
<td>129.7290</td>
<td>117.8212*</td>
<td>2.36e-06*</td>
<td>-4.4426*</td>
<td>-3.9965*</td>
<td>-4.2711*</td>
</tr>
<tr>
<td>3</td>
<td>138.9092</td>
<td>10.8974</td>
<td>3.34e-06</td>
<td>-4.1098</td>
<td>-2.9945</td>
<td>-3.6809</td>
</tr>
</tbody>
</table>

The criterion were significant when the lag length was 1. In this study, the natural logarithm is the largest and SIC as well as AIC are the smallest, therefore 1 is the optimal lag period.

Data Stability Test

We estimated the TVP-VAR-SV model for three variables, with parameters estimated through MCMC sampling. The basic idea is to initialize the parameters using priori distributions, then to estimate the posterior conditional probabilities of the parameters by sampling the posterior distributions through
the MCMC method and finally to perform time-varying impulse response analysis. Empirically, we set the number of draws to 22,000, eliminating 2,000 pre-treatments of burnt samples, selecting the 1st order lag.

Note: The table shows the results of the MCMC parameter regression. The row elements for $sb1$, $sb2$, $sa1$, $sa2$, $sh1$, and $sh2$ correspond to the first and second diagonal elements of the matrices $\Sigma_\beta$, $\Sigma_a$, and $\Sigma_h$, respectively. Columns in the table include the mean, standard deviation, 0.95 confidence interval, Gelman-Rubin diagnostic, and null factor. It was Geweke (1992) who proposed the convergence diagnostics proposed, whose original assumption was that the parameters converge to the posterior distribution. In general, an invalid impact factor of less than 100 is considered acceptable. The Geweke test CD statistic is calculated as:

$$CD = \frac{\bar{x}_0 - \bar{x}_1}{\sqrt{\sigma^2_0/n_0 + \sigma^2_1/n_1}},$$

where $\bar{x}_j = \frac{1}{n} \sum_{i=m_j}^{m_j+n_j-1} x^{(i)}$, $x^{(i)}$ is the $i$-th draw. $\sqrt{\sigma^2_j/n_j}$ is the standard error of $\bar{x}_j$ for $j = 0, 1$, respectively. If the sequence sampled by MCMC is stationary, its distribution converges to the standard normal.

Table 4 reports the quantitative diagnostics obtained after parameter estimation. Based on our findings, the results of the Geweke tests are all lower than 1.96, indicating that the original hypothesis that the parameters converge to the posterior distribution cannot be rejected at the 5% significance level, and that pre-burn sampling in the iteration cycle can effectively cause the Markov chain to converge. Additionally, the invalid factors are generally small, with a maximum value of 60.36, which is within the generally acceptable range of 100. A total of 20,000 random samples were taken by MCMC during the calculation, and a maximum of 331 (20,000/60.36) unrelated samples were obtained. According to Nakajima’s original paper, the sample was considered sufficient for making posterior inferences. None of the results of the Geweke test could reject the original hypothesis that the estimated parameters converge to a posteriori standard distribution. This indicates that the results of the parameter estimation have a high degree of validity.

### Robustness Tests

We conducted the robustness tests on the MCMC samples. The results of the specific parameter estimation tests are presented in Table 5.

In all the three tests, the pre-burn sampling in the iteration cycle was effective in making the Markov chain converge. However, the inefficiencies varied. The maximum values of the invalidation
factor after the three sampling settings were 64.27, 61.63, and 79.83, respectively. Smaller values indicate more valid samples and better sampling. Therefore, we selected an appropriate number of sampling occasions.

Table 5 Robustness tests

<table>
<thead>
<tr>
<th>Number of samples drawn (pre-burned)</th>
<th>11000 (1000)</th>
<th>33000 (3000)</th>
<th>44000 (4000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
<td>Geweke</td>
<td>Ineffective Factor</td>
<td>Geweke</td>
</tr>
<tr>
<td>sb1</td>
<td>0.958</td>
<td>3.420</td>
<td>0.992</td>
</tr>
<tr>
<td>sb2</td>
<td>0.334</td>
<td>5.610</td>
<td>0.895</td>
</tr>
<tr>
<td>sa1</td>
<td>0.386</td>
<td>31.070</td>
<td>0.436</td>
</tr>
<tr>
<td>sa2</td>
<td>0.219</td>
<td>13.420</td>
<td>0.960</td>
</tr>
<tr>
<td>sh1</td>
<td>0.467</td>
<td>47.450</td>
<td>0.015</td>
</tr>
<tr>
<td>sh2</td>
<td>0.095</td>
<td>64.270</td>
<td>0.067</td>
</tr>
</tbody>
</table>

Figure 6 shows the distribution of MCMC estimates, and the three rows of subfigures indicate the results of the sample autocorrelation function, sample path, and posterior probability density, respectively. Based on the results in the figure, the autocorrelation coefficients of the samples obtained after excluding the pre-burn-in period decreased significantly, and the autocorrelation of the samples converged to zero as the number of simulations increased, indicating that the sampling effectively eliminated the autocorrelation between the samples; meanwhile, the sample paths had no apparent fluctuations, indicating that the MCMC sampling with pre-set parameters obtained effectively correlated samples. Based on the above tests, the data met the criteria for the TVP-VAR-SV model to be applicable.

Figure 6. MCMC parameter estimation
RESULTS ANALYSIS

Time Varying Parameter-Stochastic Volatility Analysis

The TVP-VAR-SV model obtains the posterior probability density of institutional investors’ stock-holding strategies, private information transmission among institutions, and stock market trends by setting time-varying parameters with stochastic perturbations. As shown in Figure 7, its time-varying nature can be divided into three distinct periods: stable, upward, and shock.

Figure 7. Posterior random fluctuations of variables

Note: The model results are derived from the software OXMetrics 6.0, and are labelled on the timeline for each of the three phases, along with a note on the right side for the China A-share market during the sample period.

Stable Period (2006-2012): There were no major changes in the common shareholding strategies of institutional investors during this period. This period was marked by a relatively low proportion of institutional holdings and a lack of market identification. Volatility in the inter-institutional transmission of private information was very limited, and the inter-institutional channel was also relatively low. In both cases, stability is apparent. During the economic crisis of 2008, the volatility of China’s SSE Composite Index reached its peak then declined rapidly, remaining low and stable. During 2011 and 2012, the regulatory authorities took steps to curb insider trading.

Upward Period (2013-2016): The two indicators for institutional investors went from low to high, and the hold-ups became increasingly evident. The Chinese stock market experienced the onset of a bull market followed by a bear market during this period. Specifically, the regulatory authorities...
introduced a series of reform policies and launched the Growth Enterprise Market in 2014. Due to the experience of a bull market in the A-share market, speculative psychology in the market swelled rapidly. As a consequence of loose monetary policies, leveraged funds ignited the market frenzy. In order to stop the frenzy, the regulatory authorities took steps to curb over-the-counter placements. During the second half of 2015 and 2016, the stock market conditions were not promising.

Shock Period (2017-2021): The stochastic volatility of both institutional co-holding strategies and information transmission is relatively high, with the former showing more ups and downs. In 2017, institutional volatility was relatively stable in terms of strategy, but it peaked in terms of information transmission due to the recognized polarization of the Chinese stock market. The larger the market capitalization of an individual stock, the greater is its rise. There is an increase in the time-varying nature of private information because of the changing nature of the stock market, and there is a lot of noise in the market, and private information is highly variable. However, the value and efficiency of this information are limited, both in terms of actual action and market performance. The concept of group-holdings has been frequently discussed in the market, attracting the attention of investors, market regulators, and academics, with the stochastic volatility of institutional holdings is at an all-time high. In the fourth quarter of 2020, fund positions were high, reflecting a warming and activity in the context of a sluggish A-share market, which lowered the volatility of the noise component of private information.

Hence, the stochastic volatility of institutional investors’ group holding strategies and private information transmission gradually increase over the time. The stochastic volatilities of the two are not identical or even opposite. The efficiency of private information in a bear market is limited. Strong regulatory measures affect the volatility of position strategies, since they are public signals to the market and do not affect the volatility of private information among institutions. This volatility can only be balanced out by value investing. The above conclusions can be further validated by impulse response analysis.

Time Varying Impulse Response Analysis

In this section, we analyse two types of impulse responses: first is the impulse response generated by positive shocks of one unit standard deviation at different lead times, which are selected to be 4, 8, and 12 periods ahead, respectively. The other is the impulse response generated at different time points, which are chosen to be the second quarter of 2008, the second quarter of 2015, and the first quarter of 2019, which correspond to the economic crisis of 2008, the tail end of the policy bull market of 2015, and group holdings of 2019, respectively, although other settings remain consistent for the two responses.

Different Advance Periods

Figure 8 shows the impulse response results for 4, 8, and 12 periods ahead. The graphs show that the number of periods ahead varied, but the corresponding trends were broadly consistent. This indicates that the model is robust in portraying the impact of institutional holding strategies and private information transmission on A-share movements. Sub-figures (A) and (B), respectively, illustrate the lagged impact of positive shocks to the broad market trend index for Institutional Shareholding Strategy ($II_{hold}$) and Private Information Spread ($II_{info}$), respectively. For a more comprehensive view of the data, we place the broad market index trend graph in the lower part.

According to Figure 8, the impact of institutional investors’ shareholding strategies and the dissemination of private information on the stock market can also characterized by the following phases:

Stable Period: The response of the behavioural strategy of institutional investors to stock market shocks ($\varepsilon_{II_{hold}} \rightarrow index$) decreases as the lead time increases, while the response of the behavioural strategy of private information transmission to stock market shocks ($\varepsilon_{II_{info}} index$) increases as the lead time increases. The response of institutional investors’ shareholdings to stock market shocks
declined rapidly following the economic crisis of 2008, then turned negative before bottoming out. In response to stock market shocks, private information transmission accelerated. The two phenomena had opposite effects during the downturn in the Chinese stock market. The institutional shareholding strategy of private information transmission has a larger effect numerically.

Upward Period: The Chinese stock market entered a leveraged bull market during this period. This has been a period of sector rotation and hotspots, and the money-making effect has been widespread. Investors have embraced IT and the mobile internet sector has experienced a high market capitalization. The blue bar graph in Sub-figure (A) shows that the response coefficient of the institutional investors’ holding strategy to the market trend is negative and peaks at \( \varepsilon_{\text{IIhold} \rightarrow \text{index}} \). The blue bar graph in Sub-figure (B) shows that the response of the trading noise of private information transmission to stock market shocks is at its peak \( \varepsilon_{\text{IIinfo} \rightarrow \text{index}} \). The noise trade of informal news is more optimistic and speculative, fuelling the broad market sentiment. At this point the, group holding approaches the 0-axis after policy adjustments, reducing both the selling pressure and optimistic news resulting from speculation. This illustrates the importance of government regulations on the securities market.

Shock Period: In recent years, the Chinese stock market has experienced several shocks, where it is difficult to earn money and there are non-negligible investment risks. Consumer sectors, such as liquor have generally performed well during this period. The red bar graph in Sub-figure (A) shows that institutional investors’ shareholding strategy has responded positively to stock market shocks for the first time since 2018 \( \varepsilon_{\text{IIhold} \rightarrow \text{index}} \), as the concept of group holding stocks as individual stocks has a certain market appeal and drives the general market. During these two years, the group holdings typically had a macro background, investment logic and performance support. According to the red bar graph in Sub-figure (B), the response of private information to stock market shocks drops to a local trough. This suggests that value investing and risk aversion groups will dampen the impact of inside information. Institutional holdings can contribute to positive stock market trends \( \varepsilon_{\text{IIinfo} \rightarrow \text{index}} \). However, these groups are not necessarily so positive. For example, at the beginning of 2021, the market was dominated by a buzz about group holdings. Contrary to the trend of private information,
the response of institutions to stock market shocks changed from positive to negative in advance, and went all the way down. Between the two, there is a difference between ‘news’ and ‘holding’. Besides arbitrage, the market is also affected by policy adjustments, industry space, and objective trends.

In conclusion, institutional investors’ shareholding strategies do not necessarily boost equity market trends, and may even have a negative impact. This negative impact is a continuation of the specific phenomenon of ‘copying’ or ‘herd mentality’ (Sornette, 2002) in the Chinese market. The influx of institutions, particularly in a bull market with a leveraged structure, may exert pressure on the market. During a market downturn, however, market-compliant group holdings can have a positive impact on the stock market. In contrast, news circulating from within institutions, which essentially fuels stock market trends, generally has a positive impact. In a bull market with a leveraged structure, private information may spill over and significantly agitate the market. There is no market effect during market downturns, especially when the direction of investment is clear. Furthermore, holding real money is much more effective in terms of influencing the response factor than ‘blowing the trumpet’.

Different Time Points

Figure 9 shows the impulse response results for the second quarter of 2008, the second quarter of 2015, and the first quarter of 2019 at three points in time. According to the graphs, the corresponding impulse response functions for the 2008 economic crisis, the tail end of the 2015 policy bull market, and the 2019 group holding move differently. It reveals heterogeneity in the relationship between institutional holding strategies and private information transmission trends. This is also consistent with actual economic laws and financial phenomena. Sub-figures (A) and (B) illustrate the impact of positive shocks to the two variables, Institutional Shareholding ($II_{hold}$) and Private Information Transmission ($II_{info}$), on the broad market trend index. For a more comprehensive view of the market trends in the same period, we include the broad market index trend graph at the bottom of the chart. As shown in Figure 9, the impact of institutional investors’ shareholding strategies and private information transmission on the stock market can be characterized at several points in time:

First, during 2008, the impact of institutional investors’ holdings shocks on the stock market ($\varepsilon_{II_{hold}} \rightarrow \text{index}$) was more volatile, with a rapid downward impulse response function that changed from playing a supportive role to fleeing the fire quickly, and remained so until the fourth period. Meanwhile, the impact of private information spread on the stock market ($\varepsilon_{II_{info}} \rightarrow \text{index}$) is also highly volatile, with private information spreading rapidly until the fourth period, when it slows down. However, neither converges to the zero-axis. It shows the long-term impact between the institutional behaviour of the Chinese stock market and the general market movement under the impact of the global economic crisis in 2008.

Figure 9. Time varying impulse response results
Second, during the 2015, the impact of institutional investors’ holdings on the stock market ($e_{II\text{hold}} \rightarrow \text{index}$) remained negative throughout the leveraged bull market, declining at first, then increasing, and finally converging on the horizontal axis. This indicates that stocks and sectors with a high concentration of institutions did not exhibit the effects of group holding warming in a leveraged bull market, but experienced greater selling pressure, which affected the market index. Simultaneously, the impact of private information transmission on the stock market ($e_{II\text{info}} \rightarrow \text{index}$) increased rapidly and peaked in the fourth period. This bull run is associated with noise trading and speculative behaviour among institutions owing to the transmission of private information, which generates informal news.

Third, in the first quarter of 2019, the impact of institutional investors’ holdings on the stock market ($e_{II\text{hold}} \rightarrow \text{index}$) was almost negligible and the impact of private information transmission on the stock market ($e_{II\text{info}} \rightarrow \text{index}$) was relatively positive. This suggests that there are only real group holding stocks when institutional investors and other long positions are bottoming out and, information transmission has reached a relatively rational stage. When the general market performance warms up, if the group holding stocks are the type of stocks with good performance and support, the general market trend is relatively steady, and the influence of the two on the general market fluctuations will be relatively stable.

In summary, the impulse impact of institutional investors’ holding strategies varies considerably across market states and representative points in time. Private information transmission among institutions is biased towards optimism, and its response function has a positive effect on the market. Moreover, the extraordinary economic crisis had a profound impact on the relationship between institutions and the stock market. In a leveraged bull market, the impulse effects of both institutional common ownership strategies and information spreads within the market are substantial and divergent in nature. This may be attributed to the fact that the use of information transmission channels to spread optimistic news may have a negative impact on the holding strategy due to the sell-off. Markets, when they are relatively cool, can instead hold value stocks and other factors that can stabilize it.

**Linkage Mechanisms**

Figure 10 shows the impulse impact of institutional investors’ shareholding strategies coupled with private information transmission; Sub-figures (A) (B) show the results of the impulse responses for 4, 8, and 12 periods ahead, while Sub-figures (C) (D) show the impulse responses for three different points of time in Q2 of 2008, Q2 of 2015, and Q1 of 2019. Sub-figures (A) and (C) show the time-varying impulse response curves for private information transmission ($II\text{info}$) in response to a one-unit exogenous positive shock to institutional investors’ shareholding strategy ($II\text{hold}$) for the lead period and three time points, respectively. Sub-figures (B) and (D) show the time-varying impulse response curves for institutional investors’ shareholdings strategy ($II\text{hold}$) in response to a one-unit exogenous positive shock to private information transmission ($II\text{info}$) for the ahead period and three point-in-time shocks, respectively. Accordingly, Figure 10 depicts the three types of lead time in the same direction, specifically it appears that:

First, in terms of timeliness, the response values to a positive institutional investors’ holding strategy shock to private information transmission ($e_{II\text{hold}} \rightarrow II\text{info}$) vary over the three ahead periods. The greatest impact was observed in the four advance periods. Additionally, the opposite also holds true for ($e_{II\text{info}} \rightarrow II\text{hold}$). This demonstrates the significant impact of the relationship between institutional investors’ behaviour and information in capital markets in the short-term.
Second, in terms of time axis, Sub-figure (A) has largely positive response values, while Subfigure (B) has negative response values. The impact of the connection between institutional investors’ holdings and the spread of private information prior to 2013 has been reversed. Due to competitive relationships, institutional convergence in holding the same stocks reduces the spread of private information among peers. Information transmission has led to a reduction in institutional investors’ shareholdings, resulting in a clear competitor profile during this period. Following 2013, the trend in response values between the two is consistent, with some cooperative elements. It relates to the effectiveness of the crackdown on insider trading in 2012-2013. Therefore, Sub-figure (A) shows that the period in which the group holding stocks drive the market up is based on the fact that most of these stocks are value stocks and the response values were only negative during 2019-2020. This period is characterized by a significant number of collaborators and is the only period of value stock investment, where the private information transmission is least affected by the holding strategy.

Third, in terms of representative time points, the global financial crisis of 2008 was intense, widespread, and had least convergent as well as diffuse trends. Both the second quarter of 2015 and the first quarter of 2019 had similar characteristics. Sub-figure (C) illustrates that shocks to institutional investors’ shareholding strategies lead to rapid declines in internal private information transmission, whereas the entry of external peers in the group network does not result in the growth of channels for information transmission, reflecting competitiveness. Sub-figure (D) indicates that shocks to the spread of private information within an institution can result in a rapid decline in ownership strategies. While it is not possible to determine why this is the case in the model, based on the previous section, it is possible to speculate whether it stems from risk aversion or arbitrage on news, which converges to zero in the long run.

In summary, there is a distinct difference in the direction of interaction between the group holding strategy of institutional investors and the transmission of private information. The former is positive for the latter and the latter is negative for the former, with both convergent to zero over time. The two differ in terms of the magnitude of their response coefficients, with the former consisting of real money purchases and the latter consisting of delivery of information; therefore, the former has
a much greater impact on the latter. There is heterogeneity in the interaction between the two across different market states and points in time.

CONCLUSION

Research Findings and Policy Implications

It is important to note that the Chinese stock market differs from other stock markets in developed countries in terms of trading systems, issuance rules, and regulatory regimes; therefore presenting some unique phenomena in its development process. The stability of the stock market and its movement are heavily dependent on the behaviour institutional investors, one of the biggest participants in the market. Traders with heavy positions often manage the market through their decision-making behaviour, and it is mostly a collective, interconnected behaviour rather than individual behaviour that impacts the market. Therefore, this paper performs a Shannon entropy measure of complex networks by examining the group and social behaviour of institutional investors, the related strategies, and information spread. We use the TVP-VAR-SV model to analyse institutional and stock market movements to provide policy recommendations that would help in preventing large fluctuations in the Chinese stock market.

This paper finds that the time-varying nature of institutional investors’ group holding strategies and private information transmission have become more active in recent years. Using the response function in order to examine their relationship with the stock market, the former may not necessarily contribute to stock market trends and may have a negative impact. The latter, however, may boost the stock market and have a positive impact, as it seems that the news spillovers are always optimistic. Additionally, they are asymmetrical in terms of stage of development and heterogeneous in terms of market conditions. It is evident that the global economic crises had a profound impact on the relationship between institutions and the stock market. Further, high institutional holdings can exert pressure on the market in leveraged bull markets. Optimistic news emanating from institutions at this time is may have spilled over and fuelled the market higher. As a result, the phenomenon of ‘Saying One Thing and Doing Another’ is evident. Only when the market is low do the institutions comply with the market to group holding, and the internal news spread has little impact. Asymmetry and heterogeneity are reflected between the two markets as well themselves. Based on the above findings, this study makes the following suggestions:

First: from the perspective of the research hypothesis, this paper classifies investors’ group holding aberration behaviour into two factors, behavioural strategy and information transmission, using entropy in the network as a measure;

Second: from the perspective of empirical models, the TVP-SV-VAR model is used to empirically analyse the sources of shocks to trend volatility in the secondary market of securities from the structure of market participants;

Third: from the perspective of the content and the results, the analysis is carried out in terms of timeliness, timeline and representative points in time, seeking the dynamic decision mechanism between irrational noise trading and value investment in different market contexts.

According to our extensive literature review, we have not yet found any relevant literature using density entropy and structural entropy in network systems for the study of investor behaviour and information transmission, and therefore this paper is innovative in terms of methodology, analytical perspective and conclusions.

Discussions and Outlooks

Historically, classical theories that have been repeatedly questioning over the years (Ellsberg, 1961), combined psychology with finance to highlight investors’ decision biases and preferences (Daniel & Tversky, 1979). Investor behaviour influences asset prices, arbitrage, and wealth flow between
bounded rational and irrational investors, even going beyond behavioural science to encompass social
finance (Hirshleifer, 2015). Stock markets, in which institutions hold significantly more money than
individual investors, and the rise of their grouping behaviour is an important phenomenon that should
be explored. This study takes full account of economic reality by placing it within the theoretical
context of the limited rationality hypothesis and information asymmetry. Using network technology
and Shannon entropy, this study investigates the socialization of holdings. It is true that institutions
sometimes invest because of the value factor, the group holding phenomenon is a convergence to value.
The asset price diverges from its value if institutions make investments because of noise or market
speculation. Both scenarios are possible and may result in an increase in the spread of institution's
investment consequences. Our approach in this article is more pragmatic, focusing on the relationship
between the group holding phenomenon and the market. From an attribution perspective, if institutional
holding makes the market more volatile, then it is not a convergence of values, and the stock market is
not a casino, therefore such behaviour may not be conducive to the development of the stock market.

Moreover, institutional groups tend to have private information and are more informed traders
(Collin-Dufresne & Fos, 2015). Information is distributed in contrast to strategy. Private information
may mitigate information asymmetries in the market, or private information may not be true, or
private information that can be disseminated may not be true, or private information that spills over to
individual investors may not be true. In contrast to focusing on the difference between such information
and ‘gossip’, we take a pragmatic view of what dissemination of information in the group holding
phenomenon does to the market and analyse it in terms of the market outcomes.

Although there are some limitations to this study, it also indicates that future research will be
fruitful. The following are the main limitations:

First, our main focus has been on the relationship between institutional investors and the market.
We have not distinguished between the different kinds of institutions. There are subtle differences
between public and private funds, as well as between commercial and social security fundamentals,
but such a detailed analysis is beyond the scope of this study. It may be necessary to examine this
in more detail.

Second, we do not refer to public information since it would obscure the study’s objective. We
examined private information as institutional investors are informed traders. Institutional investors
may not understand public information in the same way as private information. Moreover, public
information is more symmetrical and does not incur additional cost. Would they corroborate private
information, and therefore have a more profound impact than they would have otherwise? Certainly,
this is an important question to be considered.

Finally, the ‘real money’ investment behaviour of institutional investors is much more powerful
than ‘gossip’ and is likely to have a different impact on stock market movements, both of which are
undoubtedly motivated by the desire to profit from market news. Furthermore, it is an insight into
the gaming strategies of the other half of the market, individual investors, and a challenge for the
market managers to achieve market stability.
REFERENCES


**ENDNOTES**

1 CNINFO (http://www.cninfo.com.cn) is the information disclosure website designated by the China Securities Regulatory Commission to provide information regarding listed companies. In order to assist investors in the capital market, the platform provides content functions, such as announcements, information, interaction, and online voting at shareholders’ meetings.

2 The CSMAR database provides economic data in many categories. Currently, it is one of the most authoritative databases for research in Chinese research institutions and universities.
## APPENDIX 1

### Table A. Process data on the shareholding behaviour of institutional investors

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Note: 1. Crawl samples: The crawl sample is the number of rows of the sample, and each row of data information includes the name of the institution, the category of the institution, the shareholding code, the stock abbreviation, the number of shares held in the outstanding shares, the market value of the holdings and the ratio.

2. Group holding details: We cleaned and processed the data, removed corporate shareholders and adjusted the thresholds to obtain the number of shares they held together, and the number of institutions that participated in group.

3. Descriptive statistics of shareholding ratio: We use the stocks that are held in group for each period as ID, and provide descriptive statistics on the aggregate proportion of institutional group holdings by individual stocks.