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Stock Market Liberalization and Institutional Investor Clique Behavior: Evidence from China

Muzi Jiang[1,*], Ping Yang[2]

[1] The Open University of Sichuan, China

[2] Southwestern University of Finance and Economics, China

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*Corresponding Author: Muzi Jiang(muzi.jiang@foxmail.com)

Abstract. This study examines how stock market liberalization affects the clique behavior of domestic institutional investors, distinguishing hotspot clustering from value clustering. Using panel data on Chinese listed firms from 2011 to 2019 and a difference-in-differences design, we identify institutional cliques with the Louvain community detection algorithm, and we apply large language models to cross-validate clique measurement and to construct a cross-border thematic similarity index. We find that stock market liberalization significantly reduces hotspot clustering while promoting value clustering. The inhibitory effect on hotspot clustering is more pronounced for speculative stocks, whereas the promotion of value clustering is stronger among industry leaders. These effects operate through improved market efficiency, optimized institutional holding structures, and enhanced cross-border narrative alignment. Institutions that prioritize fundamental analysis achieve superior investment returns. This study advances research on institutional cliques by integrating large language models into clique measurement and identifies a channel through which foreign investors mitigate short-term speculation in emerging liberalizing markets.

Keywords: *stock market liberalization; domestic institutional investors; clique behavior; hotspot clustering; value clustering.*

1. Introduction

Stock market liberalization has been widely studied for its effects on the global economy [1,2], stock market efficiency [3], information environment [4,5] and corporate behavior [6-8].

However, the role of foreign investors in liberalizing stock markets remains controversial. Foreign capital may enhance market efficiency by curbing domestic opportunism [9], yet it can also introduce instability through positive feedback trading in emerging markets [10]. Prior studies document herding tendencies among domestic institutional investors in China [11], but the influence of foreign capital participation on their trading behavior remains largely unexplored.

China progressively liberalized its financial sector through the Shanghai-Hong Kong Stock Connect (2014) and the Shenzhen-Hong Kong Stock Connect (2016), collectively termed stock market liberalization. Unlike earlier QFII and RQFII schemes, this reform allows foreign capital to trade A-shares anonymously via a centralized platform with fewer quota restrictions [6]. Consequently, foreign ownership in the A-share market reached 8.5% of free-float market value by 2019, making foreign investors the largest institutional group (see Figure 1). Notably, foreign capital has consistently outperformed the market by prioritizing fundamentals1, eroding the speculative advantage of domestic institutional investors. As all investors are profit-driven, whether domestic institutional investors adopt similar strategies requires further empirical investigation.

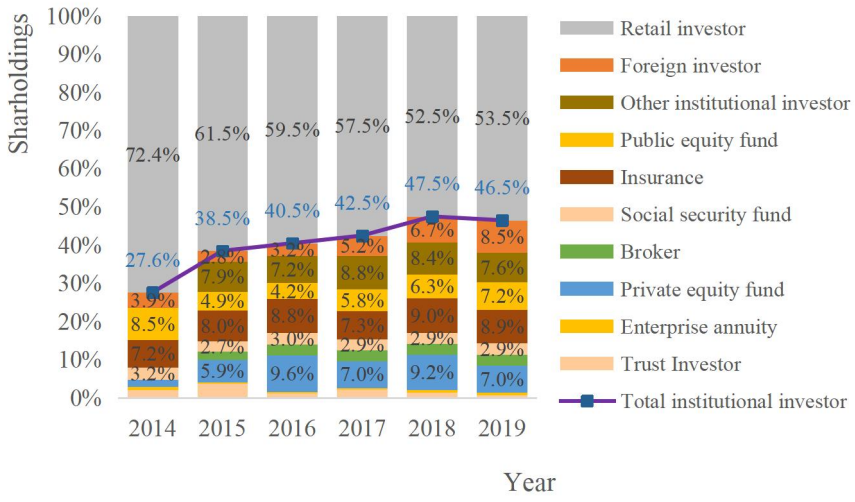

Figure 1. The percentage of market value held by various types of investors in A-shares (free float market value).

Notes: This figure illustrates the percentage of market value held by various types of investors in A-shares from 2014 to 2019.

[1] Among the top 500 stocks with the highest northbound holdings, the share of those with a return on equity (ROE) exceeding 15% grew from 20% in 2017 to 30% in 2019. Meanwhile, foreign capital trading via the Shanghai-Hong Kong Stock Connect was the only investor group to achieve consistent profits from 2014 to 2017.

Institutional investors often engage in interconnected trading to influence corporate policies [12,13]. In China, they frequently co-hold equity, forming 'institutional cliques' based on shared information [14]. These cliques enhance information dissemination and collective governance influence through voting power or exit threats [15]. Such clustering is not unique to emerging markets. In the U.S., top actively managed funds concentrate holdings in major tech firms, such as Facebook, Amazon, Apple, Microsoft, Netflix, Google. However, such cliques are often criticized for exacerbating agency problems and herding behavior [14,16,17]. In fact, their impact on market efficiency depends largely on whether they pursue quality assets or speculative trends. Distinguishing between these clique types is therefore crucial for assessing the implications of stock market liberalization for market stability.

To address these research questions, we classify clique behavior based on stock holding characteristics, corroborating institutional groupings through large language model (LLM)-based textual analysis of public disclosures. Hotspot clustering refers to cliques favoring stocks with high media attention; value clustering reflects a preference for stocks with strong fundamentals. To capture cross-border information spillover, we construct a thematic similarity index via LLM-based semantic analysis of matched domestic and foreign research reports. Using a staggered difference-in-differences model and a sample of Chinese listed firms from 2011 to 2019, we empirically examine how stock market liberalization influences these two clique types among domestic institutional investors. The results reveal that liberalization reduces hotspot clustering while promoting value clustering. Specifically, liberalization mitigates hotspot clustering in speculative stocks and fosters value clustering in industry leaders. These effects are driven by improvements in market efficiency and institutional holding structures. Liberalization reduces mispricing and opportunistic collusion in hotspot stocks; it also enhances the informational quality of value stocks and extends holding periods. Moreover, domestic investors who prioritize fundamental analysis over speculative trading tend to achieve superior returns.

Our research makes the following contributions. First, we identify stock market liberalization as a channel for cross-border information exchange. While existing studies primarily explore information exchange within social networks—such as geographic proximity [18], alumni connections [19] or co-ownership networks [20], we show that domestic institutional investors emulate foreign investors by shifting toward fundamentally valuable assets, enriching resource dependency theory [21].

Second, we advance the literature on institutional clique behavior by distinguishing hotspot

from value clustering. While prior research has largely examined institutional investor networks in corporate governance and firm value [14,15,22,23], the drivers of different clustering behaviors remain underexplored. Incorporating LLM-based validation and cross-border thematic similarity measures, we enhance understanding of investor dynamics under liberalization and offer a framework for identifying clique types.

Third, our study sheds light on mitigating the short-term clique behavior of domestic institutional investors. Volatility in emerging markets is often driven by retail investors' irrational trading [11,24]. We demonstrate that domestic investors adjust strategies by observing foreign investors' focus on fundamentals, providing new evidence on the benefits of market liberalization for developing economies.

2. Hypothesis development

China's capital market is dominated by retail investors [24], who often purchase attention-grabbing stocks without thorough fundamental analysis [25]. While retail investors may profit from such speculative trading, the widespread preference for hotspot investments encourages domestic institutional investors to exacerbate market fluctuations [26,27], even when fully aware of the overvaluation [28-30]. Given environmental differences, foreign capital may maximize returns by either aligning with speculative trends [31] or adopting fundamental trading [32], thereby influencing domestic institutional clique behavior in distinct ways.

On one hand, foreign capital's bubble-chasing may incentivize domestic institutions to form speculative cliques, namely hotspot clustering. China's stock market has long exhibited speculative tendencies, with valuations diverging from fundamentals [33,34]. Within this environment, foreign investors may engage in positive feedback trading or momentum investing to capture excess returns [30,35]. Sophisticated investors often strategically time overvaluation corrections rather than directly counteract mispricing [36]. Moreover, institutional investors' network advantages enhance bargaining power, fostering collaboration with corporate managers [14,37]. This collusion amplifies domestic investors' influence, enabling coordinated exits to maximize private gains. Consequently, stock market liberalization may exacerbate volatility and mispricing, encouraging hotspot clustering for speculative returns.

Meanwhile, under performance evaluation pressures and market rankings [16,38], domestic institutional investors may rationally mimic peers' decisions [38,39]. If foreign capital targets short-term gains in hotspot stocks, domestic institutions are likely to follow suit. This herding behavior reduces intra-group competition and impedes private information integration into

stock prices [14]. Consequently, domestic institutional investors engage in hotspot clustering, forming speculative cliques around hotspot stocks. Based on this, we propose the following hypothesis:

H(a): Stock market liberalization stimulates domestic institutional investors to engage in hotspot clustering rather than value clustering.

On the other hand, foreign capital's value investment philosophy encourages domestic institutional investors to cluster around higher-value stocks. Unlike earlier liberalization policies (e.g., QFII and RQFII), current reforms relax restrictions on foreign capital, enhancing its trading impact [40]. This creates an ideal platform for foreign capital to correct mispricing and curb managerial opportunism [41]. Extensive evidence indicates that foreign institutions typically adopt rational, long-term strategies that reduce speculation [42,43]. As a result, domestic institutional investors are less likely to profit from mispriced stocks and thereby attenuating their hotspot clustering.

Moreover, foreign investors from developed markets possess superior investment experience and information processing capabilities [44]. Their portfolio returns often reflect the integration of firm-specific fundamental information into trading strategies [45]. Liao et al. [32] further suggest that northbound inflows, by incorporating firm fundamentals, reshape domestic investors' trading behavior. Consequently, domestic institutional investors are motivated to emulate foreign capital's value-oriented strategies to achieve superior returns.

Resource dependency theory posits that network members access information through social learning and intra-network communication [21,46]. As foreign capital trading increases the costs of hotspot clustering for domestic institutional investors, domestic institutional investors shift towards fundamental trading. Consequently, these investors and their peers abandon speculative strategies in favor of collective approaches focused on long-term, higher returns, thereby clustering more around value stocks.

Thus, we propose a competing hypothesis as follows:

H(b): Stock market liberalization stimulates domestic institutional investors to engage in value clustering rather than hotspot clustering.

3. Data and research design

3.1. Data

As SH-HK Stock Connect started in 2014 and SZ-HK Stock Connect in 2016, our full sample covers the period from 2011 to 2019 to ensure symmetry in the three years before and after the

shock, excluding the effect of the epidemic. Data on shareholdings of listed companies are from WIND database, and the dynamic eligible shares traded under the Stock Connect programs are collected from Hong Kong Exchanges and Clearing Limited (HKEX). Data for media reports are from China Research Data Service (CNRDS). Other financial data are from CSMAR database. The sample covers six domestic institutional investor types: fund management companies, securities firms, insurers, social security funds, trust companies, and financial companies. We exclude ST, ST, and PT firm-year observations and those with missing values. Continuous variables are winsorized at the 1st and 99th percentiles. The final sample comprises 17,020 observations.

3.2. Variable definition

3.2.1. Institutional investor clique

Following Crane et al. [47], we identify institutional groups by linking institutions based on common holdings in the fourth quarter of each year. A clique exists if each domestic institutional investor holds at least a 5% stake in a common firm by year-end. Specifically, off-diagonal elements are set to one if both institutions in a pair hold at least a 5% stake in the same firm, and zero otherwise. This procedure yields an N×N binary matrix of institution-to-institution connections. We then import the matrix into Gephi and apply the Louvain algorithm [48] to extract institutional communities. Figure 2 presents the resulting cliques in 2019: nodes of the same color connected by edges represent investors within the same clique. Information flows more readily within cliques, and this facilitates network communication. However, the absence of shared holdings among other institutions makes coordination more challenging.

Then, we calculate three measures as follows:

$$CliqueHold_{i,t} = \sum_{j=1}^{n} \lambda_{i,j,i} \times Clique inst_{i,j,t} \tag{1}$$

$$CliqueTop_{i,t} = Max\{CliqueSum_{k,i,t} | k \in M\} \tag{2}$$

$$CliqueHerf_{i,t} = \sum_{j=1}^{M} \lambda_{i,j,t} \times \left(CliqueSum_{k,j,t}\right)^2 \tag{3}$$

where λ is an indicator variable equal to one if institution i belongs to a clique j at time t. N represents the total number of institutional investors within the investor group in year t. $Clique inst_{i,j,t}$ represents institution i's ownership percentage in firm j at time t. $CliqueSum_{k,i,t}$ is the total proportion of tradable shares of stock i held by group k in year t. $CliqueHold_{i,t}$ is the total fraction of the firm owned by all cliques. $CliqueTop_{i,t}$ represents the total ownership

share held by the single clique with the largest stake in firm i. $CliqueHerf_{i,t}$ is calculated as the sum of the squared ownership fractions of all cliques with holdings in firm i, reflecting the concentration of ownership across cliques.

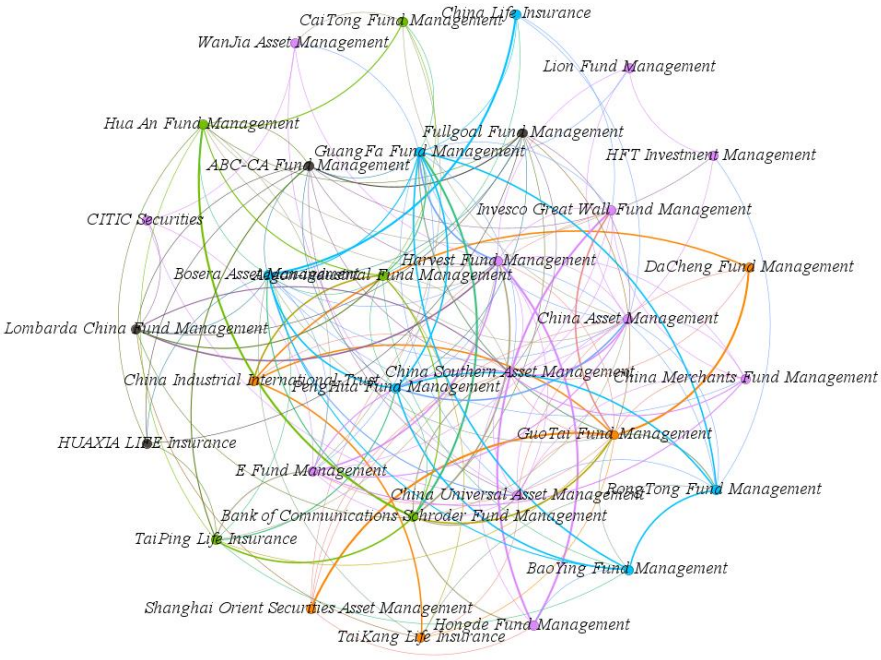

Figure 2. Example of a clique in 2019.

Notes: This figure presents the network of domestic institutional investors in 2019 based on the institutional shareholdings data. Each dot of the same color represents institutional investors belonging to the same clique.

3.2.2. The hotspot stock

Extant literature indicates that the media sentiment triggers investor overreactions [49] and significantly impact financial markets through individual investors' stock trading [50]. We propose that stocks with more media coverage tend to attract higher investors' attention. The development of the Internet has made online media an important channel for investors to obtain information. Therefore, we use the natural logarithm of 1 plus the total number of positive news reports on company i by online media in the year t to measure its hotspot degree.

$$Hotspot_{i,t} = \ln\left(1 + PositiveNews_{i,t}\right) \tag{4}$$

3.2.3. The value stock

We measure a firm's fundamental value using the moving weighted average of its return on equity (ROE) over the past three years (Value). ROE is defined as net profit margin × total asset turnover × equity multiplier, capturing a firm's profitability, asset efficiency, and financial

leverage more comprehensively than single financial indicators. However, prior research suggests that ROE can be manipulated by management [51], and relying solely on a single-year measure may introduce distortions. Thus, we adopt a three-year moving weighted average to provide a more stable assessment of a firm's fundamental value.

3.2.4. LLM applications in variable validation and behavioral classification

To enhance the construct validity of core variables and uncover the micro-level information transmission mechanism of stock market liberalization, we introduce large language model (LLM) techniques as a methodological complement to traditional quantitative analysis. We apply LLM in two logically connected dimensions: (1) cross-validating the accuracy of Louvain-based institutional clique identification; (2) constructing a cross-border thematic similarity index to distinguish between value and hotspot clustering, and to serve as a proxy for the information spillover channel.

3.2.4.1. Validity check of institutional clique identification.

Traditional community detection based on common shareholdings identifies co-holding groups but cannot verify whether these groups reflect actual institutional coordination with consistent investment logics. To address this, we adopt a two-stage LLM framework. In Stage 1, we extract structured attributes from 12,743 institutional quarterly reports, holding announcements, and investor meeting minutes. Using GPT-4 (temperature = 0.3), we parse each institution's disclosures to identify three core attributes: stated investment style, sector allocation preferences, and documented co-investment patterns. In Stage 2, we feed these vectors into the model for unsupervised community division, with the model blinded to the original network results. We then calculate the Jaccard similarity between LLM-identified groups and Louvain-derived cliques. The average annual similarity reaches 0.782 and is significant at the 1% level, confirming that our network-based measurement accurately captures real-world institutional coordination.

3.2.4.2. Construction of cross-border thematic similarity index.

Grounded in resource dependence theory [52], institutions engaging in value clustering should exhibit narrative convergence with foreign investors, whereas those engaging in hotspot clustering should show divergence. We construct a cross-border thematic similarity index via LLM-based text analysis to verify this theoretical distinction.

(1) Sample and data

We focus on the top 30 stocks with the largest northbound holdings each quarter and collect

two matched sets of research reports at the stock-quarter level: quarterly investment commentaries from 17 major global asset managers (e.g., BlackRock, Vanguard) and quarterly research reports from the top 50 Chinese mutual fund companies. Only report pairs covering the same stock in the same quarter are retained to ensure contemporaneous information sets.

(2) LLM-based analytical procedure

Table 1. LLM Applications in Variable Measurement and Validation

Application Module	*Specific Procedure*	*Model Configuration*	*Core Purpose and Output*
1. Institutional Clique Validity Check	Stage 1: Structured attribute extraction	GPT-4, temperature = 0.3	Extract 3 investment attributes from institutional disclosures: investment style, sector preference, co-investment patterns
	Stage 2: Unsupervised grouping & cross-validation	GPT-4, temperature = 0.3	Conduct blind independent community division; calculate Jaccard similarity with Louvain cliques to verify construct validity
2. Cross-Border Thematic Similarity Construction	Step 1: Fundamental rationale extraction	GPT-4o, temperature = 0.3	Extract top 3 core fundamental investment reasons from each report, filtering out sentiment and technical analysis
	Step 2: Semantic vectorization	1536-dimension LLM embedding model	Convert textual rationales into standardized semantic vectors; compute average vectors for domestic and foreign samples by stock-quarter
	Step 3: Similarity quantification	Cosine similarity algorithm	Calculate cosine similarity between averaged domestic and foreign vectors as the final thematic similarity score
	Step 4: Regime classification	ROC curve method	Determine optimal threshold of 0.62; classify samples into high-alignment (value clustering) and low-alignment (hotspot clustering) regimes

We adopt a three-step framework based on GPT-4o. In Step 1, we extract the top 3 core fundamental investment rationales from each report via a standardized prompt, explicitly excluding market sentiment, technical analysis, and market timing. The prompt is specified as:

"You are a professional financial analyst. Extract the top 3 core fundamental reasons for recommending or holding this stock from the following research report. Focus only on company-specific fundamentals (e.g., earnings growth, market share, technological innovation, governance quality) and industry-level factors. Do not include technical analysis, market timing, or sentiment-based arguments. Output the results in a numbered list format."

In Step 2, we convert each extracted rationale set into a 1536-dimensional semantic vector

via LLM embedding. We compute separate average vectors for foreign and domestic reports by stock-quarter. In Step 3, we measure thematic similarity as the cosine similarity between these two averaged vectors for each stock-quarter observation.

(3) Threshold determination and regime classification

We identify the optimal similarity threshold of 0.62 via the receiver operating characteristic (ROC) curve method, which achieves the strongest discriminant validity between the two clique types. Observations above 0.62 are classified into the high-alignment regime, corresponding to value clustering where domestic narratives align closely with the fundamental-focused investment logic of foreign institutions. Observations at or below 0.62 are classified into the low-alignment regime, corresponding to hotspot clustering where domestic institutions tend to prioritize non-fundamental market factors. This data-driven threshold provides an objective, empirically grounded boundary for distinguishing value clustering from hotspot clustering.

Table 1 summarizes all LLM-based procedures, model configurations, and corresponding outputs across the two application modules.

3.2.5. Stock market liberalization

First, we define the dummy variable Treat, which equals 1 if the firm is listed on the SH-HK or SZ-HK Stock Connect, and 0 otherwise. We then create the dummy variable Post, which equals 1 if the firm is included in either program in the current or any subsequent year, and 0 otherwise. Finally, we construct the interaction term HSSC by multiplying the Treat and Post variables.

3.3. Methodology

To test hypothesis, we examine the impact of the stock market liberalization on domestic institutional investors' clique behavior. Namely, whether stock market liberalization stimulates domestic institutional investors to engage in hotspot clustering or value clustering.

$$Clique_{i,t} = \alpha_0 + \alpha_1 HSSC_{i,t} + \alpha_2 Hotspot_{i,t} + \alpha_3 HSSC_{i,t} \times Hotspot_{i,t} + \alpha_4 \sum Control_{i,t} + \gamma_l + \eta_l + \varepsilon_{l,l} \quad (5)$$

$$Clique_{i,t} = \beta_0 + \beta_1 HSSC_{i,t} + \beta_2 Value_{i,t} + \beta_3 HSSC_{i,t} \times Value_{i,t} + \beta_4 \sum Control_{i,t} + \gamma_2 + \eta_2 + E_{2,2} \quad (6)$$

Where $\text{Clique}_{i,t}$ represents the institutional investor clique and is measured by $\text{CliqueHold}_{i,t}$, $\text{CliqueTop}_{i,t}$, and $\text{CliqueHerf}_{i,t}$, respectively. $\text{HSSC}_{i,t}$ is a dummy variable equal to 1 if the listed firm is eligible for trading after stock market liberalization, and 0 otherwise. $\text{Hotspot}_{i,t}$ is the natural logarithm of 1 plus the total number of positive news reports on company i by online

media in the year t, capturing the stock's hotspot degree. $Value_{i,t}$ is the moving weighted average of return on equity of stock i over the previous three years, capturing the stock's fundamental value. The interaction term of HSSC×Hotspot assesses the impact of liberalization on clique behavior toward hotspot stocks, while the interaction term of HSSC×Value captures the impact toward value stocks. We control for size, age, leverage ratio, revenue growth, turnover, largest shareholding ratio, management ownership, board independence, CEO duality, and state ownership. We also include firm fixed effects and year fixed effects. Variable definitions refer to Table 2.

Table 2. Variable Definition

Variable	*Definition*
	Variables used in the baseline regression and robustness checks
Clique	The institutional investor clique that is represented by $CliqueHold_{i,t}$, $CliqueTop_{i,t}$, $CliqueHerf_{i,t}$ separately. $CliqueHold_{i,t}$ is the total fraction of the firm owned by all cliques. $CliqueTop_{i,t}$ represents the total ownership share held by the single clique with the largest stake in the firm. $CliqueHerf_{i,t}$ is the sum of the squared ownership fractions of all cliques with holdings in the firm.
HSSC	A dummy variable equal to one 1 if the listed firm is eligible for trading under either the SH-HK or SZ-HK Stock Connect Program, and 0 otherwise.
Hotspot	The natural logarithm of 1 plus the total positive news about firms.
Value	The moving weighted average of return on equity for the previous three years.
Size	The natural logarithm of a company's total asset at last fiscal year end.
Lev	Company's leverage, calculated as the ratio of total liabilities to total assets at last fiscal year end.
Growth	The growth rate of total sales at the end of last fiscal year.
Age	The natural logarithm of the number of days since the company has listed plus 1.
Turnover	The annual average monthly turnover rate of the firm.
Mhold	The percentage of outstanding shares held by the CEO at the end of last fiscal year.
Indd	The percentage of independent directors in the board at the end of last fiscal year.
Dual	A dummy variable equal to one if the CEO is also chairman of the board and zero otherwise.
Top1	The number of shares held by the largest shareholder divided by the total shares.

SOE	A dummy variable equals one if the firm is the state-owned company and zero otherwise.
Hh_Hv	*Hh_Hv* equals 1 if the stock belongs to both a high hotspot and high value group and zero otherwise.
Hh_Lv	Hh_Lv equals 1 if the stock belongs to both a high hotspot and low value group and zero otherwise.
Lh_Hv	Lh_Hv equals 1 if the stock belongs to both a low hotspot and high value group and zero otherwise.
WebSearch	The natural logarithm of 1 plus the aggregated annual internet search index. The search key terms include the stock code, company abbreviation, and full company name of listed companies in China.
Tbq	Tobin's Q value equals market capitalization divided by total assets.
Other variables used in the additional analyses	
Bubble	We rank all sample stocks in each period based on their price-to-earnings ratio (PE), price-to-book ratio (PB), and price-to-sales ratio (PS) in ascending order. Bubble equals the average rank of each stock across these three variables to determine its level of speculation.
Indleader	We sort all sample stocks in each period based on their industry proportions of market capitalization (MV), revenue (Rev), and net commercial credit from suppliers (Credit) in ascending order. Indleader equals the average rank of each stock across these three variables to measure its industry status.
Misprice	The Amihud illiquidity captures the degree of stock mispricing.
InstNum	The natural logarithm of the number of institutional investor network groups at the firm level plus 1, which captures the collusion motive among institutional investors.
SYN	The stock price synchronization measures the information content of the stock.
Holdual	The weighted average of the duration (Unit: Year) that institutional investor clique member i holds stock j continuously.
CAR5_5	The cumulative excess returns calculated around days [-5,5] near the announcement date of the annual report.
BHAR	The annual buy-and-hold abnormal returns.

4. Empirical analyses

4.1. Descriptive statistics

Table 3 presents the descriptive statistics. HSSC has a mean of 0.250, indicating that Stock

Connect-eligible firms account for 25% of the sample. The mean values of CliqueHold, CliqueTop, and CliqueHerf are 4.1%, 2.5%, and 0.2%, respectively. These relatively low shareholding proportions suggest limited direct voting power for cliques. Consequently, they may rely on trading activities to fulfill their governance role.

Table 3. Descriptive Statistics

Variable	*N*	*Mean*	*S.D.*	*Min*	*Median*	*Max*
CliqueHold	17020	0.041	0.060	0.000	0.015	0.528
CliqueTop	17020	0.025	0.037	0.000	0.010	0.299
CliqueHerf	17020	0.002	0.007	0.000	0.000	0.111
HSSC	17020	0.250	0.433	0.000	0.000	1.000
Hotspot	17020	4.359	1.044	1.946	4.344	7.258
Value	17020	0.069	0.084	-0.309	0.073	0.265
Size	17020	22.238	1.347	19.742	22.065	26.060
Lev	17020	0.432	0.207	0.050	0.421	0.916
Growth	17020	0.183	0.449	-0.576	0.106	3.038
Age	17020	7.864	1.080	3.807	8.135	9.146
Turnover	17020	0.560	0.570	0.045	0.369	3.155
Mhold	17020	0.110	0.191	0.000	0.001	0.685
Indd	17020	0.384	0.106	0.000	0.375	0.667
Dual	17020	0.264	0.441	0.000	0.000	1.000
Top1	17020	0.359	0.148	0.088	0.341	0.750
SOE	17020	0.394	0.489	0.000	0.000	1.000

4.2. Baseline results

4.2.1. Hypothesis testing

Table 4 presents the impact of stock market liberalization on the characteristics of domestic institutional investors' clique behavior. In Columns (1)-(3), the coefficients on HSSC×Hotspot are statistically negative at 5% or lower. In Columns (4)-(6), the coefficients on HSSC×Value are statistically positive at 5% or lower. These results indicate that stock market liberalization reduces the speculative tendencies of the domestic capital market, encouraging institutional investors to form value-based cliques rather than hotspot-driven ones. This finding aligns with hypothesis H(b).

Table 4. Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)
	CliqueHold	*CliqueTop*	*CliqueHerf*	*CliqueHold*	*CliqueTop*	*CliqueHerf*
HSSC×Hotspot	-0.0089***	-0.0033***	-0.0005**			
	(-6.784)	(-3.917)	(-2.209)			
HSSC×Value				0.0381**	0.0354***	0.0054***
				(2.397)	(3.742)	(2.830)
HSSC	0.0403***	0.0181***	0.0030***	-0.0050**	-0.0005	0.0002
	(6.434)	(4.473)	(2.893)	(-2.516)	(-0.391)	(0.909)
Hotspot	0.0148***	0.0068***	0.0010***			
	(18.283)	(13.772)	(10.920)			
Value				0.0796***	0.0357***	0.0042***
				(8.804)	(6.402)	(4.658)
Size	0.0085***	0.0048***	0.0003**	0.0080***	0.0043***	0.0003*
	(5.891)	(5.445)	(2.186)	(5.297)	(4.726)	(1.775)
Lev	-0.0307***	-0.0203***	-0.0027***	-0.0194***	-0.0144***	-0.0019***
	(-5.758)	(-6.014)	(-4.579)	(-3.519)	(-4.142)	(-3.290)
Age	0.0006	-0.0009	-0.0003	0.0028**	0.0000	-0.0001
	(0.501)	(-1.053)	(-1.626)	(2.155)	(0.037)	(-0.770)
Growth	0.0045***	0.0023***	0.0003***	0.0053***	0.0028***	0.0004***
	(4.897)	(3.890)	(3.002)	(5.687)	(4.578)	(3.656)
Turnover	-0.0103***	-0.0056***	-0.0008***	-0.0048***	-0.0029***	-0.0004***
	(-8.674)	(-6.869)	(-5.444)	(-4.212)	(-3.807)	(-3.090)
Mhold	0.0088*	0.0062**	0.0009	0.0122***	0.0077**	0.0011**
	(1.915)	(2.041)	(1.600)	(2.662)	(2.561)	(2.061)
Indd	0.0074	0.0040	0.0003	0.0069	0.0037	0.0003
	(1.617)	(1.334)	(0.568)	(1.489)	(1.224)	(0.509)
Dual	0.0018	0.0015	0.0001	0.0022	0.0016*	0.0002
	(1.191)	(1.516)	(0.837)	(1.402)	(1.672)	(0.963)
Top1	0.0125	0.0126*	0.0024*	0.0063	0.0092	0.0020
	(1.194)	(1.942)	(1.931)	(0.592)	(1.428)	(1.584)
SOE	-0.0096	-0.0043	0.0000	-0.0097	-0.0043	0.0000
	(-1.620)	(-1.328)	(0.045)	(-1.607)	(-1.332)	(0.020)
_cons	-0.1744***	-0.0829***	-0.0045	-0.1285***	-0.0572***	-0.0013
	(-5.401)	(-4.160)	(-1.417)	(-3.870)	(-2.794)	(-0.403)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	17020	17020	17020	17020	17020	17020
Adj. R2	0.102	0.068	0.029	0.085	0.061	0.024

Notes: Standard errors are corrected by clustering at firm level and t-statistic reported in the parentheses. ***, **, and * denote statistical significance at 0.01, 0.05, and 0.1, respectively. The same applies to all subsequent tables unless otherwise noted.

4.2.2. Consider both hotspot and value

Certain stocks exhibit characteristics of both hotspot and value. We classify the sample into four groups based on the industry-year median of Hotspot and Value, and define three corresponding dummy variables: Hh_Hv equals 1 for high-hotspot and high-value stocks; Hh_Lv equals 1 for high-hotspot and low-value stocks; Lh_Hv equals 1 for low-hotspot and high-value stocks. The low-hotspot and low-value group (Lh_Lv) serves as the benchmark. We

interact these three dummies with HSSC in Model (7) to examine differential effects across groups.

$$\begin{aligned} Clique_{i,t} &= \alpha_0 + \alpha_1 HSSC_{i,t} + \alpha_2 Hh_Hv_{i,t} + \alpha_3 Hh_Lv_{i,t} + \alpha_4 Lh_Hv_{i,t} \\ &+ \alpha_5 HSSC_{i,t} \times Hh_Hv_{i,t} + \alpha_6 HSSC_{i,t} \times Hh_Lv_{i,t} + \alpha_7 HSSC_{i,t} \times Lh_Hv_{i,t} \\ &+ \alpha_8 \sum Control_{i,t} + \gamma_i + \eta_t + \varepsilon_{i,t} \end{aligned} \quad (7)$$

In Table 5, the coefficient on HSSC × Hh_Lv is significantly negative, while that on HSSC × Lh_Hv is significantly positive. The coefficient on HSSC × Hh_Hv is significantly negative only in Column (1). These results indicate that stock market liberalization significantly reduces institutional investor clustering in high-hotspot, low-value stocks while promoting clustering in low-hotspot, high-value stocks, yet has no significant effect on high-hotspot, high-value stocks.

Table 5. Further Differentiation in the Main Test

	(1)CliqueHold	*(2)CliqueTop*	*(3)CliqueHerf*
HSSC×Hh_Hv	-0.0122***	-0.0022	-0.0006
	(-3.432)	(-0.969)	(-1.075)
HSSC×Hh_Lv	-0.0170***	-0.0087***	-0.0015***
	(-6.019)	(-4.731)	(-3.840)
HSSC×Lh_Hv	0.0062*	0.0040*	0.0007*
	(1.838)	(1.794)	(1.717)
HSSC	0.0066**	0.0049***	0.0012***
	(2.375)	(2.632)	(2.857)
Hh_Hv	0.0265***	0.0109***	0.0015***
	(13.304)	(8.662)	(6.460)
Hh_Lv	0.0096***	0.0045***	0.0006***
	(6.713)	(4.738)	(4.105)
Lh_Hv	0.0041**	0.0018	-0.0002
	(2.305)	(1.561)	(-0.758)
_cons	-0.1362***	-0.0635***	-0.0018
	(-4.294)	(-3.223)	(-0.546)
Controls	Yes	Yes	Yes
Firm_FE	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes
N	17020	17020	17020
Adj. R²	0.100	0.067	0.029

Notes: Control variables are included in all specifications but suppressed in the table to conserve space; full results are available from the corresponding author upon request. The same applies to all subsequent tables unless otherwise noted.

4.3. Alleviating endogeneity problems

4.3.1. Propensity score matching

To address potential self-selection bias, we conduct a robustness check using Propensity Score Matching (PSM). Following Chen et al. [53]; Xiong et al. [40], we match each treated firm with a non-treated firm using baseline control variables. Specifically, we apply 1-to-1

nearest neighbor matching with a 0.01 caliper and no replacement. After matching, no significant difference remains and bias falls below 10%, indicating comparable pairs. We then re-estimate the baseline models using the matched sample. Table 6 shows that the coefficients on HSSC×Hotspot are significantly negative at the 5% level or lower in Columns (1)–(3), while those on HSSC×Value are significantly positive at the 1% level in Columns (4)–(6). These findings suggest that the baseline results are robust to sample selection bias.

Table 6. Robustness: Baseline Regression Using Propensity Score Matched Sample

	(1) *CliqueHold*	*(2)* *CliqueTop*	*(3)* *CliqueHerf*	*(4)* *CliqueHold*	*(5)* *CliqueTop*	*(6)* *CliqueHerf*
HSSC×Hotspot	-0.0056***	-0.0027**	-0.0005**			
	(-2.862)	(-2.023)	(-2.169)			
HSSC×Value				0.0711***	0.0552***	0.0106***
				(2.993)	(3.499)	(3.628)
HSSC	0.0279***	0.0160***	0.0036***	-0.0017	0.0004	0.0005
	(3.225)	(2.765)	(3.366)	(-0.552)	(0.186)	(1.442)
Hotspot	0.0135***	0.0069***	0.0009***			
	(11.654)	(8.901)	(6.341)			
Value				0.0560***	0.0279***	0.0019
				(4.393)	(3.290)	(1.177)
_cons	-0.2187***	-0.1302***	-0.0131**	-0.1674***	-0.1005***	-0.0100
	(-4.626)	(-4.129)	(-2.220)	(-3.395)	(-3.070)	(-1.640)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6866	6866	6866	6866	6866	6866
Adj. R²	0.445	0.366	0.319	0.434	0.360	0.316

4.3.2. Parallel trend test

To draw valid causal inferences, the DID model must satisfy the parallel trend assumption. We use the model below to examine the dynamic effects of the stock market liberalization on the domestic institutional investors' clique behavior, focusing on hotspot and value stock clustering separately.

$$\begin{aligned} CliqueHold_{i,t} = {} & \beta_0 + \alpha_1 Pre_{-k} \times Treated \times Hotspot + \alpha_2 Post_k \times Treated \times Hotspot \\ & + \alpha_3 Pre_{-k} + \alpha_4 Post_k + \alpha_5 Hotspot + \gamma Control_{i,t} \\ & + \sum Firm + \sum Year + \varepsilon_{i,t} \end{aligned} \tag{8}$$

$$\begin{aligned} CliqueHold_{i,t} = {} & \beta_0 + \beta_1 Pre_{-k} \times Treated \times Value + \beta_2 Post_k \times Treated \times Value \\ & + \beta_3 Pre_{-k} + \beta_4 Post_k + \beta_5 Value + \gamma Control_{i,t} \\ & + \sum Firm + \sum Year + \varepsilon_{i,t} \end{aligned} \tag{9}$$

where Pre-k/Postk (T = 0, 1, or 2) equals 1 if the year is T year(s) before/after the

implementation year, and 0 otherwise. The estimates of α_1 and β_1 are insignificant, indicating no significant difference in clique behavior between the treated and control groups before the stock market liberalization. Additionally, the estimates of α_3, α_4, β_3, and β_4 suggest the stock market liberalization significantly impacts the clique behavior of domestic institutional investors after the first year of policy implementation. Figure 3 presents the parallel trend test, supporting the validity of the parallel trend assumption.

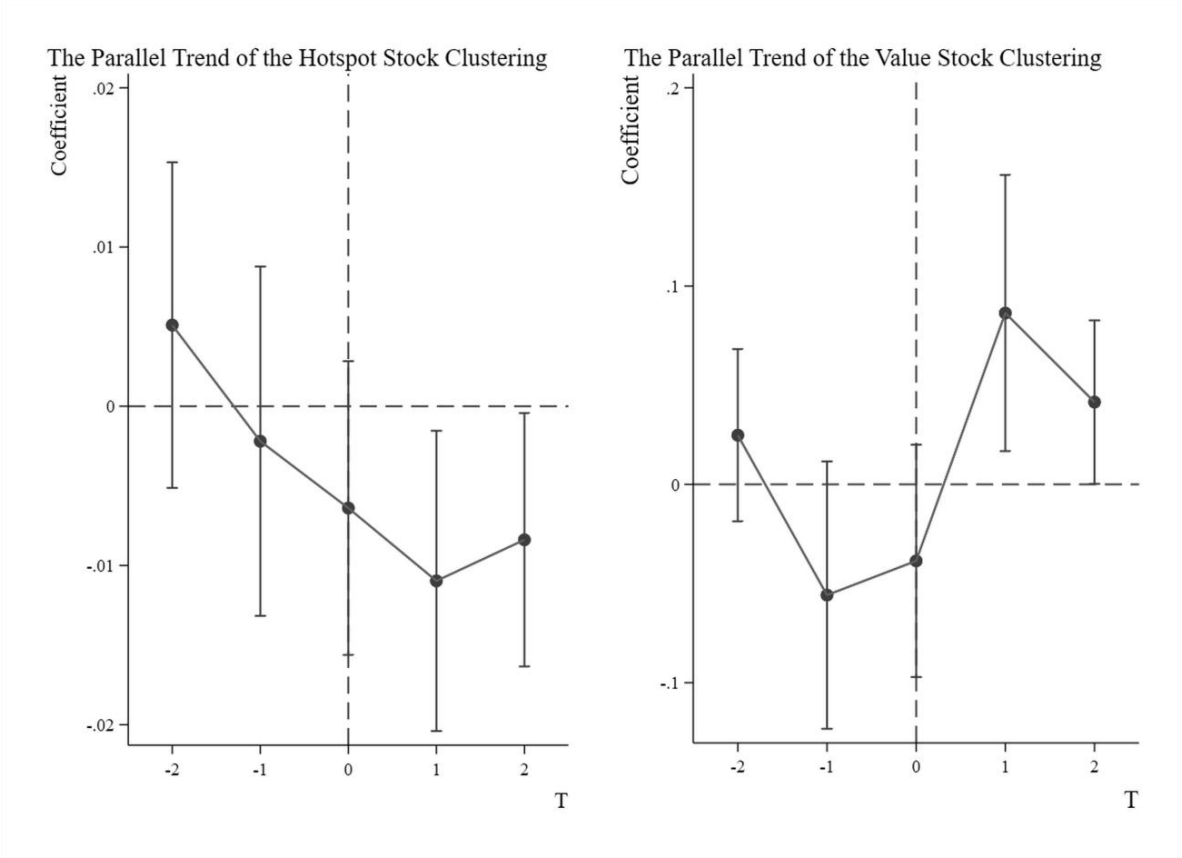

Figure 3. Parallel trend assumption.

Notes: This figure presents the point estimates and 95% confidence intervals for the dynamic effects of the stock market liberalization on the clique behavior of domestic institutional investors concerning hotspot and value stocks individually.

4.4. Other robustness checks

We conduct robustness tests through sample filtering, variable substitution, and network criteria adjustments. First, to address potential pre-existing foreign investor influence, we exclude QFII-held samples and companies with simultaneous 'A+H shares' listings. The results are presented in Columns (1) and (2) of Table 7. Second, we substitute the hotspot and value measures. Hotspot stocks are identified using the aggregated annual internet search index (WebSearch), including the stock code, company abbreviation, and full company name. Firm value is measured by Tobin's Q (Tbq). The results are shown in Columns (3) and (4) of Table

7.

Table 7. Other Robustness Checks: Sample Filtering and Alternative Measures

	(1)CliqueHold	*(2)CliqueHold*	*(3)CliqueHold*	*(4)CliqueHold*
HSSC×Hotspot	-0.0089***			
	(-5.952)			
HSSC×Value		0.0705***		
		(7.618)		
HSSC×WebSearch			-0.1462***	
			(-5.485)	
HSSC×Tbq				0.0070***
				(5.241)
HSSC	0.0396***	-0.0063***	0.3843***	-0.0159***
	(5.606)	(-2.972)	(5.447)	(-5.444)
Hotspot	0.0144***			
	(16.927)			
Value		0.0540***		
		(3.048)		
WebSearch			-0.0282	
			(-1.475)	
Tbq				0.0104***
				(18.774)
_cons	-0.1989***	-0.1513***	-0.1241**	-0.3652***
	(-6.004)	(-4.459)	(-2.352)	(-10.864)
Controls	Yes	Yes	Yes	Yes
Firm_FE	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes
N	15106	15106	16186	16632
Adj. R²	0.105	0.088	0.081	0.130

Third, following Edmans and Holderness [12], we recompute clique ownership by lowering the holdings threshold. To mitigate the impact of network construction criteria, we redefine the network by requiring two institutional investors to each hold at least 3% of the same company's tradable shares. The results are presented in Table 8.

Table 8. Other Robustness Checks: Institutional Investors Clique Connectivity (3%)

	(1) *CliqueHold*	*(2)* *CliqueTop*	*(3)* *CliqueHerf*	*(4)* *CliqueHold*	*(5)* *CliqueTop*	*(6)* *CliqueHerf*
HSSC×Hotspot	-0.0090***	-0.0036***	-0.0005***			
	(-6.439)	(-4.294)	(-2.590)			
HSSC×Value				0.0461***	0.0229**	0.0035*
				(2.694)	(2.369)	(1.808)
HSSC	0.0417***	0.0181***	0.0030***	-0.0051**	-0.0008	0.0001
	(6.136)	(4.423)	(2.962)	(-2.337)	(-0.629)	(0.186)
Hotspot	0.0160***	0.0072***	0.0011***			
	(18.186)	(13.533)	(11.478)			
Value				0.0873***	0.0395***	0.0055***
				(8.697)	(6.357)	(5.095)
_cons	-0.2205***	-0.0977***	-0.0079**	-0.1687***	-0.0737***	-0.0047
	(-6.190)	(-4.583)	(-2.162)	(-4.624)	(-3.370)	(-1.235)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	17020	17020	17020	17020	17020	17020
Adj. R2	0.099	0.073	0.035	0.083	0.066	0.029

5. Additional analyses

This section further investigates the heterogeneity and underlying mechanisms through which stock market liberalization affects the clique behavior of domestic institutional investors.

5.1. Heterogeneity test

We further examine the types of clustered stocks that are either reduced or increased following stock market liberalization. Following Dass et al. [54], Bali et al. [55], and Liu et al. [56], we rank all sample stocks based on their price-to-earnings ratio (PE), price-to-book ratio (PB), and price-to-sales ratio (PS) in ascending order for each period. The average rank determines the speculation level (Bubble), with higher values indicating greater speculation, as shown in equation (10). Similarly, we rank stocks by their industry proportions of market capitalization (MV), revenue (Rev), and net commercial credit from suppliers (Credit) to measure industry status (Indleader), as shown in equation (11). Higher values indicate stronger industry leadership. Here, N is the total number of stocks in the period. Group regression is conducted by classifying stocks into bubble and non-bubble groups, as well as industry leaders and non-leaders, based on the annual median values of Bubble and Indleader.

$$Bubble_{i,t} = \frac{1}{3}(PE_N/N + PB_N/N + PS_N/N) \tag{10}$$

$$Indleader_{i,t} = \frac{1}{3}(MV_N/N + Rev_N/N + Credit_N/N) \tag{11}$$

Columns (1) and (2) of Table 9 show that stock market liberalization effectively reduces hotspot clustering for both bubble and non-bubble stocks. The coefficient of HSSC×Hotspot reveals that this weakening effect is more pronounced for bubble stocks, with a significant difference between groups at the 5% level. Columns (3) and (4) indicate that domestic institutional investors exhibit a stronger preference for value clustering with industry-leading companies after stock market liberalization. The coefficient of HSSC×Value shows a significant between-group difference at the 5% level. This suggests that foreign capital entry leads domestic institutional investors to focus more on core assets such as industry leaders.

Table 9. Additional Test: The Clustered Stock Types

	(1) *Bubble CliqueHold*	*(2)* *Non-bubble CliqueHold*	*(3)* *Indleader CliqueHold*	*(4)* *Non-Indleader CliqueHold*
HSSC×Hotspot	-0.0133***	-0.0074***		
	(-5.342)	(-4.657)		
HSSC×Value			0.0611**	0.0015
			(2.161)	(0.076)
HSSC	0.0544***	0.0311***	-0.0033	-0.0009
	(4.576)	(3.897)	(-0.946)	(-0.315)
Hotspot	0.0106***	0.0158***		
	(9.892)	(12.548)		
Value			0.0372***	0.1190***
			(3.952)	(7.358)
_cons	-0.1554***	-0.2499***	-0.1380***	-0.0039
	(-3.419)	(-4.405)	(-2.982)	(-0.056)
Controls	Yes	Yes	Yes	Yes
Firm_FE	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes
Diff (Empirical P-value)	0.020**		0.040**	
N	8434	8586	8817	8203
Adj. R²	0.093	0.115	0.089	0.119

5.2. Potential mechanisms

5.2.1. Mechanism on hotspot clustering

By evaluating long-term growth potential and selling overvalued stocks, foreign investors integrate private information into prices, driving them toward intrinsic value [53]. We argue that foreign capital inflows reduce mispricing in hotspot stocks, thereby curbing domestic institutional investors' hotspot clustering behavior. Using the Amihud illiquidity measure [60] to capture market mispricing (Misprice), Column (1) of Table 10 shows a significantly negative coefficient on HSSC×Hotspot. This indicates that stock liberalization reduces mispricing in hotspot stocks and suppresses hotspot clustering.

Previous literature suggests that medium- to large-sized shareholders may collude to

expropriate other shareholders' interests [57]. When institutional investors' holdings closely align with those of controlling shareholders, collusion likelihood increases [58]. Higher concentration of institutional networks at the firm level strengthens their price influence and enhances collusion potential with major shareholders, thereby increasing the likelihood of stock price bubbles. Following Attig et al. [59], we calculate the number of institutional network groups at the firm level to capture collusion potential (InstNum). Column (2) of Table 10 reveals a significant negative coefficient on HSSC×Hotspot. This suggests that liberalization reduces hotspot clustering by mitigating collusion incentives within institutional investor networks.

5.2.2. Mechanism on value clustering

Following foreign capital entry, experienced foreign investors with standardized approaches effectively assess stock values. This improves price information integration and promotes long-term holding of value stocks.

Table 10. Mechanism Test

	(1)Misprice	*(2)InstNum*	*(3)SYN*	*(4)Holdual*
HSSC×Hotspot	-0.1011***	-0.0416***		
	(-3.768)	(-6.087)		
HSSC×Value			0.5209**	0.0115***
			(2.107)	(2.985)
HSSC	0.4199***	0.2116***	-0.0183	0.0037***
	(2.970)	(5.802)	(-0.521)	(5.470)
Hotspot	0.1695***	0.0944***		
	(6.616)	(14.607)		
Value			-0.8003***	-0.0012
			(-5.289)	(-0.445)
_cons	23.8442***	-4.5200***	1.1291**	0.0287***
	(21.628)	(-18.069)	(2.193)	(2.976)
Controls	Yes	Yes	Yes	Yes
Firm_FE	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes
N	17020	17020	17020	17020
Adj. R2	0.440	0.174	0.236	0.027

Following Morck et al. [61], we use stock price synchronization (SYN) to measure information content, where a higher value indicates lower synchronization and greater information content. Additionally, following Cremers et al. [62], we calculate the weighted average holding duration of clique members (Holdual). In Column (3) and Column (4) of Table 10, the coefficients on HSSC×Value are significantly positive. This suggests that stock market liberalization enhances the information quality of value stocks and extends holding periods, both of which stimulate value clustering among domestic institutional investors.

5.3. The returns from clique behavior

We further examine whether clique behavior improves portfolio returns through reduced hotspot clustering and increased value clustering after stock market liberalization. We measure short-term returns using cumulative abnormal returns (CAR5_5), calculated as excess returns over the [-5, 5] window around the annual report announcement. For long-term returns, we employ annual buy-and-hold abnormal returns (BHAR). Table 11 shows that the coefficients on HSSC×CliqueHold are significantly positive, indicating that stocks with higher clique ownership yield higher returns following liberalization. The reduction in hotspot clustering and the increase in value clustering after stock liberalization contribute to these higher returns.

Table 11. The Returns from Clique Behavior

	(1)CAR5_5	*(2)BHAR*
HSSC×CliqueHold	0.1467***	0.3877**
	(3.232)	(2.166)
HSSC	-0.0035	0.0067
	(-0.784)	(0.458)
CliqueHold	0.0394	1.5744***
	(1.382)	(14.378)
_cons	-0.2155**	0.7702**
	(-2.441)	(2.373)
Controls	Yes	Yes
Firm_FE	Yes	Yes
Year_FE	Yes	Yes
N	17020	17020
Adj. R²	0.061	0.429

6. Conclusions and implications

This study examines how stock market liberalization shapes the clique behavior of domestic institutional investors, distinguishing between hotspot and value clustering. To enhance construct validity, we complement network-based clique identification with large language model (LLM)-based textual analysis of institutional disclosures. We further construct a cross-border thematic similarity index from matched domestic and foreign research reports to proxy information spillover channels. Using a staggered difference-in-differences model and Chinese listed firms from 2011 to 2019, we find that stock market liberalization reduces hotspot clustering while promoting value clustering. Specifically, stock market liberalization significantly reduces clustering in high-hotspot, low-value stocks and promotes clustering in low-hotspot, high-value stocks, yet has no significant effect on high-hotspot, high-value stocks. In terms of stock characteristics, stock market liberalization mitigates hotspot clustering in speculative stocks while fostering value clustering in industry leaders. These effects are driven by improvements in market efficiency and institutional holding structures. Domestic

institutional investors achieve enhanced returns as they shift their investment strategy.

This paper presents three implications. First, stock market liberalization stimulates information exchange and transactional competition between Chinese and foreign investors. Foreign capital's value discovery and trading strategies may pressure domestic institutional investors to improve their capabilities and shift toward fundamental-based trading. The LLM-based textual evidence of narrative convergence documented in this study corroborates such cross-border social learning. Second, efforts should focus on enhancing institutional holding structures within China's capital market. Strengthening institutional investors' influence can help mitigate speculative tendencies, such as over-concentration in high-hotspot stocks, and promote more rational, value-oriented practices. Third, given that liberalization promotes value clustering in industry-leading firms, policymakers should consider targeted incentives to support innovation-driven companies. This could further attract domestic and foreign institutional investors to long-term value investments, which are crucial for China's economic transformation and technological advancement.

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