

Do Listed Companies' Technological Innovations Make Institutional Investors' "Group Holdings" More Favorable? Based on Network-Clustering

Jia Liu, Shandong University of Finance and Economics, China

Qingru Li, Chinese Academy of Social Sciences, China*

Chunyan Lin, Shandong University of Finance and Economics, China

ABSTRACT

This paper constructs a dynamic panel threshold model with a sample of firms in the Chinese A-share market. The authors analyse the non-linear relationship and the mechanisms between the two. The study found that there is an inverted U-shaped relationship between corporate technology innovation and institutional investors' group holdings and an inverse N-shaped relationship between corporate technology innovation output and institutional investors' group holdings. And when they add the innovation input to a lag operator, the model calculations are similar to the inverse N-type non-linear model of innovation output, and the two innovation indicators are consistent. When institutional investors feel the sentiment and the "pass the parcel" in the market, they will exit the group because of the risk factor. Although technological innovation in companies will contribute to their long-term development, it is important to be more aware of the risks involved. Excessive levels of investment will still be subject to external financing constraints.

KEYWORDS

Complex Networks, Corporate Technological Innovation, Institutional Investors, Network-Clustering

INTRODUCTION

Technological progress and innovation are the most enduring drivers of economic growth and important engines of competitiveness (Porter, 1992). According to data published by the World Intellectual Property Organization (WIPO), the number of international patent applications filed through the Patent Cooperation Treaty (PCT) reached 265,800 in 2019, representing an annual growth rate of approximately 5.2%. China filed 58,990 patent applications under the organization's PCT framework in 2019, surpassing the 57,840 filed by the United States, making it the country that filed the most international patent applications. This represents a 200-fold increase in 20 years compared to 1999, when the organization received 276 patent applications from China. Developed countries have been shown to outperform developing countries in economic development through science, technology, and innovation. Figure 1 shows comparisons between China and other major economies in terms of R&D expenditure and patent applications over a 20-year period—between China and East Asian countries (Japan and Korea), European countries (Germany, France, the United Kingdom, Spain,

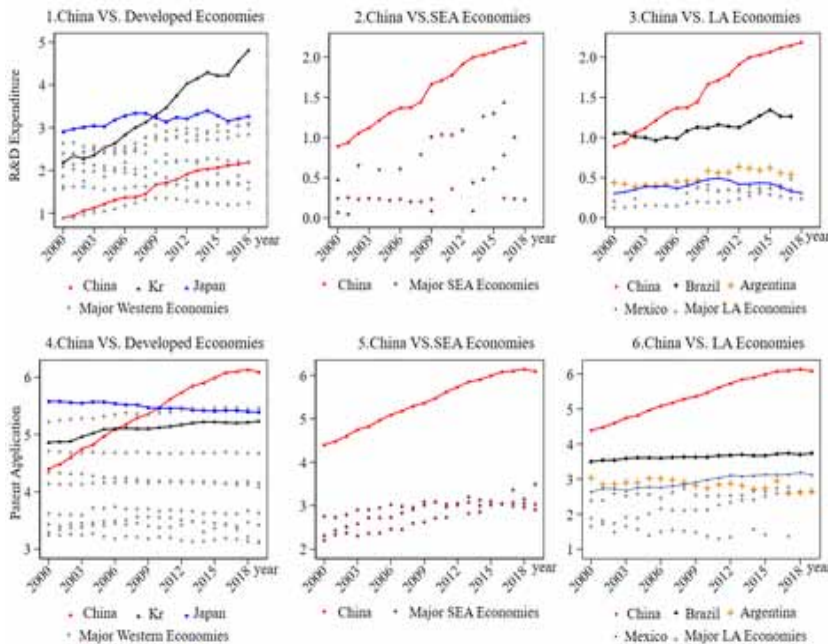
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*Corresponding Author

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Denmark, Austria), and the United States of America. The second column presents a comparison among China, Indonesia, Malaysia, and Thailand. The third column shows comparisons between China and Brazil, Argentina, Mexico, and other Latin American countries, such as Colombia, Uruguay, and Chile. Figure 1 shows that developed countries in the West have always attached importance to technological innovation and intellectual property rights, and their innovation input and output are at an advanced level in the world. East and Southeast Asian countries are also moving over time in terms of innovation development. China’s technological innovation has expanded quantitatively along with its rapid economic development and is growing at a faster rate overall. Further, China’s science and technology innovation has increased in volume along with its rapid economic development and is growing at a faster rate overall. The rate of investment in science and technology research has not slowed in recent years, although the rate of increase in the number of patent applications has decreased significantly. This phenomenon was related to the “high-quality development” after 2017. This refers to the shift in the Chinese economy from a stage of high growth to a stage of high-quality development, which fundamentally lies in the dynamism, innovation, and competitiveness of the economy. This is reflected in solving the problems related to imbalances and inadequacies faced in development by transforming the development mode, optimizing the economic structure, transforming the growth momentum, and improving the quality and efficiency of economic development holistically. Thus, innovative development is no longer merely about increasing numbers, which is manifested in a slowdown in the slope of the folding graph. In 2018, the WIPO and Cornell University published the “Global Innovation Index Report 2018,” in which China ranked 17th for the first time.

Figure 1. International comparison of innovation inputs and outputs in China



Notes: The data source for Figure 1 is the CEIC[®] China database. R&D includes basic research, applied research, and experimental development. R&D expenditure is expressed as a percentage of GDP for the total domestic expenditure on R&D of the sample. It specifically includes capital and

recurrent expenditures in four relevant sectors: business, government, higher education, and private nonprofit organizations. Patent applications are worldwide patent applications filed through the PCT process or with national patent offices. Data are in logarithmic form to avoid changing the nature of the data and relationships, achieve a compression of the scale of the variables, and reduce covariance and heteroscedasticity.

Compared to developed countries, China's overall innovation level is still large but not strong. Development of the competitiveness of technological innovation at the enterprise level is mainly due to the following: the Chinese government's macro policy of continuous optimization of the innovation environment; the introduction of many preferential policies such as technology policy and industrial policy; the meso financial market's "blood transfusion" and support to capital markets; the optimization and upgrading of capital structure; the micro perspective of the enterprises' own strategic decisions and development plans. Enterprises, especially listed companies, are important in China's market economy. Their ability to innovate does not only determine their own competitive advantage; it is also significant for the regional and national economy to achieve sustainable, high-quality growth. Therefore, it is of practical empirical significance to study the relationship between capital transfusions in the meso financial market and corporate innovation of listed companies under well-established macro policy factors.

As the main micro-economic body, asset formation in a company's innovation project is characterized by high risk, long development times, and uncertain returns, perhaps leading to a shortage of exogenous financing for the process (Hall and Lerner, 2009). Thus, external market financing is an important funding source for companies' innovation inputs (Czarnitzki and Hottenrott, 2011). In the early days of external finance research, the pecking order theory of corporate finance suggests that companies might choose credit because of lower external financing costs, and there is no need to transfer control interest and public disclosure (King and Levine, 1993). However, from the perspective of companies with financing needs, more innovative companies are more likely to use equity and bonds to finance themselves, while less innovative firms tend to use bank loans (Levine and Zervos, 1999). Beck and Levine (2002) also explored the relationship between access to finance and firm innovation, denying that bank credit has an advantage in solving firms' external financing problems. Brown et al. (2009) suggested that the United States has developed its technological innovation capabilities faster than Germany and Japan because of its well-developed stock capital markets, while Germany and Japan still exhibit a credit-based financial structure. This advantage is most pronounced in the knowledge-driven stage of development (Brown et al., 2013). Hsu et al. (2014) found that firms that use stock market financing are more innovative, whereas the opposite is true for credit financing. This shows the close relationship between exogenous capital and firm innovation, in addition to firms' capital investments. In the innovation development process, the financial system often plays an important role in facilitating the flow of capital from inefficient to efficient sectors (Wang et al., 2020). A causal link exists between corporate innovation and institutional investors (Aghion et al., 2013). Currently, the Chinese stock market is in a period where institutional investors often use funds to invest or speculate in a "group" approach so that there is even a "group stock" speculative theme. Thus, we focus our research on the relationship between the stock market and corporate innovation in the financial markets to investigate whether listed companies wishing to attract external financing can demonstrate that "if you bloom, the wind will come" through active innovation.

Using 14,140 observations involving 1,010 non-financial listed companies in the Shanghai and Shenzhen A-share markets from 2006 to 2019 as the test sample, we investigate the relationship between the technological innovation of these companies and their recognition by external institutional investors as holdout stocks. First, we reviewed the literature related to our research in two aspects: a) external financing is essential for corporate innovation, but external financing constraints objectively exist; b) gambling preferences and emotional contagion exist in the search for external institutional financing. Second, we infer through mechanistic research that institutional investors can direct capital from less innovative sectors to more efficient ones. However, there is gaming and arbitrage, and

they are influenced by sentiment. Subsequently, through preliminary studies, baseline regressions, and further research, we argue that the relationship between corporate innovation and institutional investors is complex and that there is a relationship between its complexity and market sentiment. Finally, policy recommendations are made based on the empirical findings. Specifically, our research found the following:

- a. Segmenting corporate innovation into input and output indicators, we find a significant correlation between both sets of indicators and “group holdings” among institutional investors. This relationship is not a simple linear relationship.
- b. An inverted U-shaped relationship exists between innovation investment and institutional investors’ holdings. An increase in corporate innovation investment increases institutional investors’ holdings; however, after peaking, the proportion of institutional investor holdings decreases as innovation investment continues to increase.
- c. Investor sentiment is a transmission factor between the two—innovation investment and institutional investors’ holdings. When investor sentiment for holding shares of the listed company is low, there is a negative relationship between innovation output and institutional investor holdings, with innovation indicators struggling to reverse the negative impact of market sentiment. When investor sentiment is moderate, the relationship between the two variables is positive. As market sentiment rises further and speculation on the subject matter becomes strong, stocks begin to “pass the parcel” more frequently; further, institutional investors, sensing a market risk factor instead, choose to sell.

LITERATURE REVIEW

Corporate Innovation and Financial Constraints

A close link exists between corporate innovation and exogenous capital. On the one hand, firms often need exogenous capital to innovate. Science and technology innovation activities require large-scale, long-term stable financial support because of their long cycle time and high risks, while R&D activities are expensive, making innovation-type companies pay attention to cash flow issues (He and Wintok, 2016). The innovation capital of listed companies comes mainly from the stock market as external capital, which has certain advantages (Brown et al., 2009; He and Wintok, 2016); Hall and Lerner (2009). It allows for a more efficient assessment of corporate innovation and avoids adverse selection and moral hazard problems in the financing process, thus effectively reducing the associated external financing costs for firms (Hsu et al., 2014). However, a company’s internal innovation can also affect the external stock market performance of the listed company, which is related to the interests of external investors. The high-risk nature of R&D may lead to a positive correlation between the intensity of R&D investment and volatility of a company’s stock returns (Gharbi et al., 2014). Of course, technological innovation by listed companies may also increase the expected return of individual stocks and raise the premium (Hsu, 2009). Zhou et al. (2017) found that in a study of the Chinese enterprise growth market, the more companies invest in innovation, the higher their excess returns to investors while also reducing the risk of stock price collapse. The view on stock returns, on the other hand, is controversial. The intangible risk chapters of Corrado et al. (2005) and McGrattan and Prescott (2005) used theoretical models, such as cost models and economic growth models, to conclude that innovation inputs reduce stock returns. Nevertheless, the results of several empirical studies do not support this view. Lin (2012) used a dynamic equilibrium model to obtain a covariance between R&D investment in corporate innovation and future stock returns that are positively associated. Cohen et al. (2013) suggest that the stock market underreacts to information related to corporate innovation and may overlook the interaction between the two and miss the excess. Gu (2016) showed through a real options model that firms’ R&D types tend to

be riskier, but their expected returns are higher. Of course, original innovations are more likely to generate higher stock returns (Hirshleifer and Hsu, 2020). The value generated by innovation is also limited by a country's intellectual property protection system (Belderbos et al., 2021).

Gambling Preference And Social Network Transmission

The theory that investors hold shares in listed companies because of the dynamism and value potential that comes from innovative activity is certainly good. However, the stock market is also speculative. On the one hand, gambling anomalies arise from speculative concepts or private idiosyncratic information in speculative markets, which leads to the entry and exit of investors. Empirical studies generally agree that gambling preferences exist but are not consistent across all investor types. Bailey et al. (2011) and Bali et al. (2017) argue that institutional investors are more sophisticated, have lower conceptual preferences than other individual investors, and are less susceptible to cognitive biases. They further argue that gambling preferences should be attributed to individual investors' irrational trading rather than to institutional investors. However, further research indicates that institutional investors also have gambling preferences, and Alldredge (2020) suggests that such preferences may be heterogeneous. Small-scale institutional investors and individual investors have similar gambling preferences. Moreover, Alldredge (2020) found that institutional investors' preferences are related to the state of the market. They mitigate their avoidance of lottery stocks during periods of low market sentiment, hold them ahead of individual investors, and gain arbitrage as market sentiment heats up and drives share prices higher. In a study of the Chinese market, Kong et al. (2019) found that funds prefer to invest in innovative companies and earn higher excess returns when holding cash. Zhu and Zhang (2020) found that there is a significant MAX anomaly in the Chinese A-share market; the stronger the speculative characteristics and the lower the intrinsic value of the stocks, the more significant the anomaly. Institutional investors do not correct mispricing in the Chinese stock market because of their gambling preferences. On the other hand, institutional investor behavior is communicable and interactive rather than discrete. Institutional investors in the stock market create networks of associations because of common shareholdings, and members within the network are interconnected (Pareek, 2012). These associations become important channels for investors to obtain additional information, learn, imitate the behavior of other members, and even cooperate with group characteristics and behavior. Further, there is a strong link between them and spatial autoregressive models in spatial econometrics (Bramouille and Djebbari, 2009). The probability of cooperation between individuals in these tightly connected networks is significantly higher because of their ability to transmit information effectively (Centola, 2011), especially after forming clustered but regular networks, which are more conducive to the formation, propagation, and consolidation of behavior (Centola, 2010). Arguably, information transfer and sharing among members within institutional investor networks are important mechanisms for the emergence of institutional investors' convergent behavior (Colla, 2007). Pool (2014) suggests that common shareholdings are the result of private communication among institutional investors and that there is "grouping" of institutional investor behaviors (Crane et al., 2017). Guo et al. (2020) also demonstrated the existence of institutional investor network characteristics using data from the Chinese stock market and provided some analysis of the impact of "grouping" trading patterns.

A comprehensive review of the above literature reveals that the current studies that take stock market financing as a starting point focus on the problems of listed companies investing in innovation projects, the way external financing is chosen, or whether financing can promote innovation research in companies. Studies that consider companies conducting innovation projects as a starting point mostly argue for the impact of the strategy on volatility and returns of their stocks. We consider the growing importance of innovation in the economy as a whole and its far-reaching impact on the long-term development of companies, industries, and the macroeconomy. Therefore, we use the graph clustering technique on the network as a starting point to investigate the intrinsic relationship between technological innovation and institutional investors' "group holdings" behavior in listed

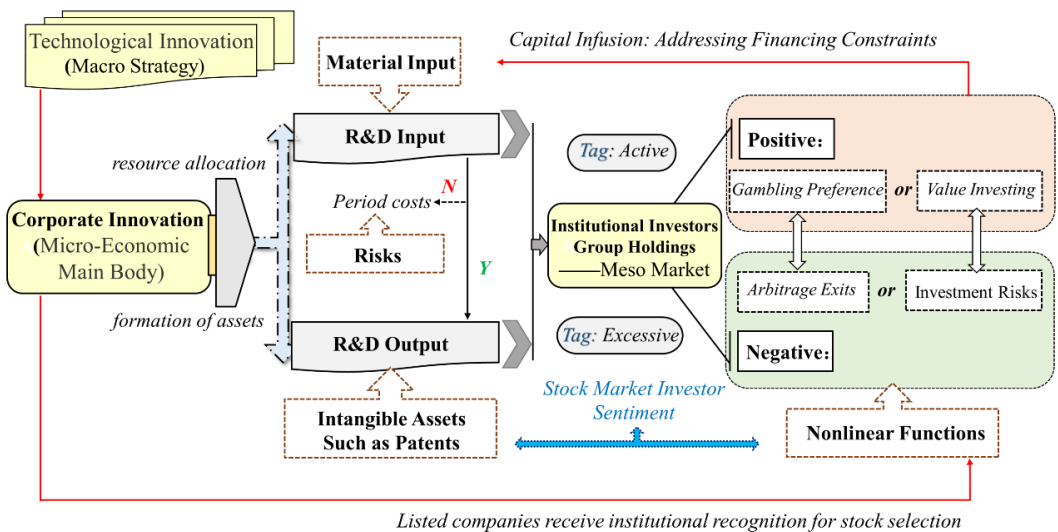
companies. We did not find any research from this perspective. In this study, we use a sample of 1,010 non-financial listed companies in Shanghai and Shenzhen A-shares from 2006–2019 to build a model for empirical data testing. The main contributions and innovations are as follows:

- From this perspective, we explore the impact of corporate innovation on institutional investors’ “group holdings.”
- In terms of technology, we use graph clustering to measure institutional investors’ “group holdings.”
- In terms of content, we investigate the nonlinear relationships (inverse U-shaped and inverse N-shaped) between the two types of indices of innovation (innovation inputs and innovation outputs).
- In terms of conclusions, we use the lag operator to test the consistency of these two types of innovation indices, both of which are inverse-N-shaped, and argue that complex functions can be attributed to market sentiment.

Mechanism Analysis and Hypothesis

China’s high-quality development has placed new demands on the quality of innovation of enterprises in the market. While the government’s macro policy continues to optimize the innovation environment, it is inseparable from the active participation of enterprises as micro market players as well as from the “blood transfusion” and support of the capital market in the meso financial market. As the main sector of the market economy, the innovation capability of enterprises, especially listed companies, determines their own competitive advantage and the deployment of national strategies. As shown in Figure 2, with the macro strategy set, it is important to examine the relationship between companies and external institutional investors using technology innovation as an opportunity.

Figure 2. Diagram showing the transmission mechanism between listed companies’ innovation and institutional investors’ group holdings



First, from the perspective of the operational mechanism for attracting external investors to innovative projects, the stock market itself has abundant liquidity and a convenient trading mechanism, which helps improve the efficiency of resource allocation in the capital market. This, in turn, helps shift more financial resources from the traditional production sector, where innovation is less efficient, to the innovation sector, where innovation is more efficient. From the perspective of a positive correlation between the two, institutional investors support corporate innovation through group holding stock selection. To this end, they use the risk reallocation function of the stock market to channel capital to innovative projects with higher risks and returns and its asset pricing function to evaluate innovative projects effectively. This may be a form of value investment; however, this is an inference that institutional investors also tend to buy overvalued stocks in their investment strategies (Jing and Kang, 2019). Further, there is an incentive and behavior to allocate to riskier speculative stocks. Therefore, this study hypothesizes that state advocacy can be translated into corporate action, which then earns the attention of institutional investors in the market, and that widespread heat may trigger market linkages that generate incentives for gambling preferences or value investing in stock selection strategies.

Hypothesis I: Innovation activity in listed companies increases the likelihood of group holdings by an institutional investor whose “group holdings” selection concerns favor listed companies labeled “Innovation Active.”

Second, from the perspective of institutional investors’ shareholdings, institutional investors or fund managers are relatively sophisticated investors and are also likely to be sophisticated arbitrageurs in the buying and selling of equity. The stock market provides this group of investors with several risk management tools, thus enabling institutional investors to invest their assets in innovative projects with higher risk and higher expected returns. This also allows them to hold conceptual and gaming stocks to reap the benefits while cashing out by attracting irrational investors—a speculation relatively rational for institutional investors themselves (Abreu and Brunnermeier, 2003). Unlike individual investors, institutional investors form complex networks because of group holdings among peers. Owing to the characteristics of the network, non-public information can be disseminated more quickly through private channels. Therefore, they can time their purchases and sales more accurately and are more likely to hold in unison. Thus, when investment in a company’s innovation projects continues to increase beyond a peak, institutional investors, whether as a result of a “group” of gambling preferences or a “coincidence” of value investment, are likely to recognize the risk of asset management and choose to clear.

Hypothesis II: Excessive innovation in listed companies reduces the likelihood of group holdings by an institutional investor whose “group holdings” selection concerns do not favor listed companies labeled “Innovation Excessive.”

Third, from a behavioral finance perspective—unlike traditional financial theory—the existence and influence of the emotional component of investors are emphasized. The emotional anomaly suggests that there are noise traders in the market and that stock trading and capital pricing are influenced by their intrinsic value and, to a large extent, by investor sentiment. Institutional investors exhibit similar trading behaviors, particularly when they hold the same stocks in groups to form relatively flat networks. Through the circulation and transmission of idiosyncratic information, the specific behavior of institutional investors may be related to the spread of information (Centola, 2011), promoting contagion to some extent so that both holding and non-holding investors exhibit communitarian, convergent behavior. Recent research on the interaction between investor sentiment and stock markets has proliferated. However, the focus of this paper is not on sentiment itself but

on listed companies that are labeled as “Innovation Excessive” or have anomalous investments in intangible assets in their financial disclosures. Whether they are branding or promoting themselves is not clear to outside investors; thus, institutional investors may also be influenced by market sentiment in their judgment.

Hypothesis III: There is a negative correlation between excessive innovation in listed companies and group holdings by institutional investors, and market sentiment is the transmission factor.

MATERIALS AND METHODS

Model Specification

The mechanism of influence between corporate innovation and external institutional investors’ holdings cannot be determined ex ante. Therefore, this study begins with a preliminary test of linear, quadratic, and moderating effects models of the relationship between the two influences. The preliminary regression expressions are as follows:

$$fundgroup_{i,t} = \alpha_1 + \beta_1 rd_{i,t} + \beta_2 control_variables_{i,t} + \delta_i + \eta_t + \varepsilon_{i,t} \quad (1)$$

$$fundgroup_{i,t} = \alpha_1 + \beta_1 rd_{i,t}^2 + \beta_2 rdinput_{i,t} + \beta_2 control_variables_{i,t} + \delta_i + \eta_t + \varepsilon_{i,t} \quad (2)$$

$$fundgroup_{i,t} = \alpha_1 + \beta_1 rd_{i,t} + \beta_2 rd_{i,t} \times threshold_{i,t} + \beta_2 control_variables_{i,t} + \delta_i + \eta_t + \varepsilon_{i,t} \quad (3)$$

Equation (1) is a linear effect test, (2) is a quadratic effect test, and (3) is a moderating effect test. Here, $fundgroup_{i,t}$ denotes the institutional investor group holding of the listed companies, and $rd_{i,t}$ denotes the technological innovation of listed companies, divided into two variables: innovation input $rdinput_{i,t}$ and innovation output $rdoutput_{i,t}$. The variable $threshold_{i,t}$ denotes if there are multiple intervals in the function, and the threshold variables are used as moderating variables for the preliminary test, where the specific variables are $invest_{i,t}$ and $dtrun_{i,t}$; further, $control_variables_{i,t}$ are the control variables. To avoid endogeneity effects caused by omitted variables, we control for individual and time in the preliminary test using double fixed effects, denoted by δ_i and η_t , respectively, and $\varepsilon_{i,t}$ is the random error term.

Equation (2) incorporates a quadratic term to test for a U-shaped relationship. In general, it is difficult to avoid multicollinearity by adding a quadratic term, and the variance inflation caused by multicollinearity increases the variance of the estimates, eventually leading to a decrease in the significance of the regression coefficients. To further capture the structural changes in the relationship between firms’ innovation and institutional investors’ group holdings, this study uses a panel threshold model. Hansen (1999) introduced the first econometric analysis of a panel threshold model with individual effects, which minimizes the sum of squares of the residuals to determine the threshold and tests the significance of the threshold, overcoming the bias of subjectively setting structural mutation points. A variable is selected as the threshold variable, and the regression model is divided into intervals based on the threshold value found. The regression equation was expressed differently for each interval, and the other sample values were grouped according to the interval of

the threshold. The coefficients were compared after regression. The baseline model is expressed as follows using a single threshold as an example:

$$\begin{aligned} fundgroup_{i,t} = & \alpha_1 + \beta_1 rdinput_{i,t} \times Ind(invest_{i,t} \leq \gamma) + \beta_2 rdinput_{i,t} \times Ind(invest_{i,t} > \gamma) \\ & + \gamma control_variables_{i,t} + \delta_i + \eta_t + \varepsilon_{i,t} \end{aligned} \quad (4)$$

$$\begin{aligned} fundgroup_{i,t} = & \alpha_1 + \beta_1 rdoutput_{i,t} \times Ind(dtrun_{i,t} \leq \gamma) + \beta_2 rdoutput_{i,t} \times Ind(assets_{i,t} > \gamma) \\ & + \gamma control_variables_{i,t} + \delta_i + \eta_t + \varepsilon_{i,t} \end{aligned} \quad (5)$$

The threshold model can therefore be abbreviated as follows:

$$fundgroup_{i,t} = \alpha_1 + \beta_1 rd_{i,t} \times Ind(\gamma) + \gamma control_variables_{i,t} + \delta_i + \eta_t + \varepsilon_{i,t} \quad (6)$$

The explanatory variables $rdinput_{i,t}$ in Equation (4) are innovation inputs, and $invest_{i,t}$ are the threshold variables for the change in the relationship between the institutional investors' holdings and the innovation inputs. The explanatory variable $rdoutput_{i,t}$ in Equation (5) is the innovation output. Variable $dtrun_{i,t}$ is the threshold at which innovation output leads to a change in the relationship between institutional investors' holdings. Thus, in Equation (6), γ is the threshold variable to be estimated, $rd_{i,t}$ and $Ind(\cdot)$ are the core explanatory variables and indicative functions, respectively, δ_i is the individual effect, η_t is the time effect, and $\varepsilon_{i,t}$ is the random disturbance.

Variable Description

Explained Variables

Group holding ($fundgroup_{i,t}$) expresses institutional investors' recognition and holding of the listed company's shares, expressed as a joint holding of stock by relevant institutions. This study uses Pareek's (2012) measurement method. Capturing data from the Shanghai and Shenzhen main boards and the reported data from fund companies, a complex network conditional on a 1% position in outstanding shares was built. In other words, a connection is established when two institutions hold more than 1% of outstanding shares in the same stock, with edges denoted by d_{ij} . Substance $\{d_{ij} | d_{ij} > 0\}$ is a network comprising an adjacency matrix, denoted by $S(d_{ij})$. Graph clustering was performed in the network using the Louvain algorithm proposed by Blondel in 2008. After clustering, the nodes of each institution were $CfundGroup(d_{ij})$. In social networks, $group(d_{ij})$ is called a community. The various institutional nodes within the clustered community are "clustered" because they hold shares in common.

In Figure 3, the two largest stock market shocks in China thus far occurred during the financial crisis in 2008 and the crash in June 2015. The study selects four time points before and after the two shocks, and Figures (A), (B), (C), and (D) generate network relationship diagrams for the second quarter of each year in 2007, 2009, 2015, and 2016, respectively. A network relationship diagram was also used as a background to mine the topology using a minimum spanning tree (MST) approach (Figure 3). After using the clustering Louvain algorithm and different group holdings, we used different colors. From the data visualization perspective in Figure 3, the network structure of institutional investors also changed significantly before and after strong stock market shocks. Before the 2007 shocks, the MST network was complex and highly correlated, indicating the prevalence and concentration of

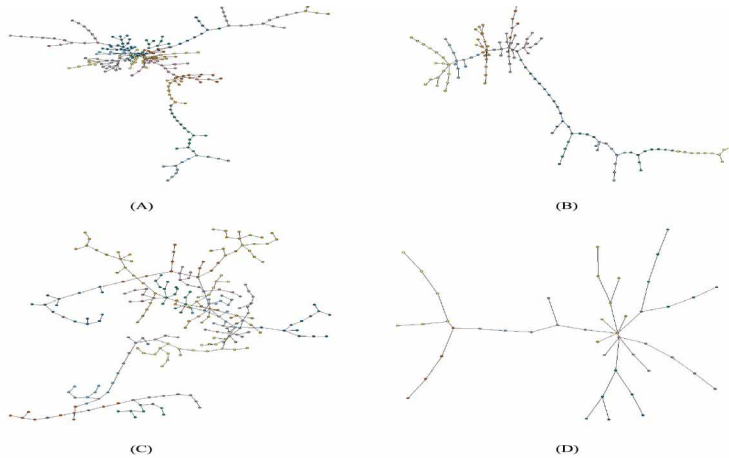
common institutional holdings. After the 2008 financial crisis, linkages between institutions due to common shareholdings significantly reduced. As the Chinese stock market evolved through shocks, the network structure was characterized by conglomerates and fragmentation between groups before the shock in the third quarter of 2015. As the MST structure was disrupted, several relatively independent and fragmented holding groups emerged after 2016. Fewer institutions participated, and the network became sparse and discrete.

Thus, graph clustering can be a good measure of institutional investors' holdings. The stocks of each listed company can be measured by the variable $fundgroup_{i,t}$, which measures the group holdings of investment, the popularity of gambling preferences, and, as an explanatory variable, the percentage of individual stock i using the formula:

$$fundgroup_{i,t} = \sum_j^n \gamma_{i,jt} X_{i,j} \quad X_{i,j} \in \{0 \cup Group(d_{ij})\} \quad (7)$$

In Equation (7), $\gamma_{i,jt}$ denotes the proportion of relevant institutional holdings in the complex network, and $X_{i,j}$ is the clustering result. The larger the $fundgroup_{i,t}$, the higher the proportion of shares chosen by the institutional investor fund, indicating a stronger willingness of external institutional investors to recognize and hold the company's shares.

Figure 3. Clustering visualization of MST networks



In the matrix data on institutional investors' stock holdings, larger weights indicate smaller distances and greater correlations between institutions. To follow the rules of the MST calculation and achieve the aim of making graphs that correctly reflect the data network relationships, pre-processing was performed using weight transformation. Figures (C) and (D) are heavily fragmented; therefore, the weights were adjusted to at least 25. To lose less data, we used a network relationship diagram when performing the actual calculation, where the data were denser and more accurate than the MST structured diagram.

Visualization through the logic of the MST calculation is matched with the shareholding characteristics of institutional investors in China. The relationship between the shareholding behavior of China's institutional investors and the overall market environment is characterized by behavioral clustering. The visualized network of institutional investors' shareholdings is characterized by one or two authoritative centers or regions in the clusters of this network system, even at more specific background points in time. This provides the basis for choosing proxy variables for our explanatory variables.

Core Explanatory Variables

Previous studies showed that innovation input or output is generally used to measure enterprises' science and technology innovation. Depending on the focus of the studies, innovation input is a relevant indicator of the investment in technological innovation of enterprises, such as funds for R&D, R&D personnel, and fixed assets. Innovation output is a measure of an enterprise's technological innovation output, including the number of patents, new products, and sales revenues from new products. The indicators of science and technology innovation of Chinese enterprises specific to this study are as follows.

- a. Innovation input $rdinput_{i,t}$ is measured by the cost incurred in the firm's R&D, reflecting factor costs and size of the firm's investment in innovation activities. This provides material security for innovations. This study uses the ratio of R&D investment to operating revenue of listed enterprises to calculate innovation investment. The larger this ratio is, the more importance the enterprise attaches to science and technology innovations.
- b. Innovation output $rdoutput_{i,t}$ of firms is determined by invention patents. Although not all innovation activities result in patents, patented technology is the most direct and effective measure of innovation output as an indicator of the ability to translate innovation into real outcomes. It reflects the output results of basic scientific and technological innovation and the economic benefits that flow to enterprises through innovation. In China, patents can be divided into design, utility model, and invention patents. Among them, invention patents are the most technically advanced, novel, and difficult to apply for. The number of invention patents reflects an enterprise's intangible assets and the market value of its innovation output. This study uses the natural logarithm of $(invention\ patents + 1)$ to measure innovation output. The larger it is, the more innovation the firm has produced.
- c. The threshold variable $invest_{i,t}$ is the threshold variable for the change in the relationship between corporate investment in science and technology innovation and institutional investors' group holdings. In this study, we take the logarithm of the R&D investment value of listed enterprises as the threshold value of $rdinput_{i,t}$ for the test of innovation investment.
- d. The threshold variable $dtrun_{i,t}$ is the threshold variable for the change in the relationship between the two as a result of institutional investors' group holdings in the company's innovation output. This study uses the average excess turnover of listed companies in processing data (*the average of the current monthly turnover rate—the average of the previous monthly turnover rate*). The results obtained from the calculation of this turnover rate can be positive or negative, indicating an increase or decrease in institutional investors' position transfer. Therefore, it is used as a test for the threshold of innovation output $rdoutput_{i,t}$.

Control Variables

The main control variables are as follows: capital expenditure ratio ($capital_{i,t}$), expressed as the ratio of the firm's capital expenditure to its total assets at the end of the year; fixed asset size ($ppe_{i,t}$), expressed as the ratio of the firm's total fixed assets at the end of the year to its total assets at the end of the year; return on assets ($roa_{i,t}$), expressed as the ratio of the firm's net profit to its total assets

at the end of the year; cash flow ($cash_{i,t}$), expressed as the ratio of an enterprise's year-end money capital to its year-end total assets; the gearing ratio ($mtb_{i,t}$), expressed as the ratio of total liabilities to year-end total assets; the GDP growth rate of the enterprise's region ($gdpr_{i,t}$), expressed as the annual growth rate of the local GDP of the prefecture-level city where the enterprise is located.

Descriptive statistics are presented in Table 1:

DATA SOURCES

Table 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Skew.	Kurt.
$fundgroup_{i,t}$	14140	0.0175	0.0398	0.0000	0.2340	2.9807	12.2859
$rdinput_{i,t}$	14140	0.0133	0.0250	0.0000	0.2183	3.0545	16.6844
$rdoutput_{i,t}$	14140	0.8034	1.8313	0.0000	8.1784	2.1101	6.0786
$invest_{i,t}$	14140	8.2478	9.0296	0.0001	22.2273	0.2134	1.1053
$dtrun_{i,t}$	14140	-0.1413	0.3542	-1.7512	1.6767	-0.5827	6.1076
$capital_{i,t}$	14140	0.0474	0.0469	0.0000	0.2721	1.6077	5.8240
$ppe_{i,t}$	14140	0.1969	0.1833	0.0000	0.7956	1.0138	3.3194
$roa_{i,t}$	14140	0.0378	0.0517	-0.4348	0.2257	-1.2937	17.1405
$cash_{i,t}$	14140	0.1267	0.1098	0.0000	0.6212	1.4756	5.3961
$mtb_{i,t}$	14140	0.0311	0.0249	0.0040	0.2759	2.7742	16.3758
$gdpr_{i,t}$	14140	0.1029	0.0350	-0.0470	0.2040	0.1839	2.8838

The shareholding ratio and details of institutional investors were obtained from the CSMAR^f database, and missing data were supplemented with fund reports and the WIND^g database. Data on corporate innovation, threshold variables, and control variables were obtained from the CSMAR database. There were significant differences between China's corporate accounting system and auditing standards after 2006. Considering data completeness and accuracy, data from the period 2006–2019 was selected as the sample for this paper^h. Large financial enterprises were excluded for decentralization; ST-type[†] enterprises were removed, and normally traded enterprises were retained. Further, stocks with less than 30 trading weeks in the annual data were excluded, and individuals with missing data were removed. A final sample of 14,140 observations was obtained from 1,010 listed companies. To avoid the influence of outliers, all continuous variables are winsorized at the 1% and 99% levels in the empirical tests in this study.

RESULTS AND DISCUSSION

Preliminary Test

Regression analysis was first performed on Equations (1), (2), and (3), focusing on the significance of the primary term, quadratic term, and fork product coefficients. The fixed effects linear regression, nonlinear regression, moderated effects regression, and correlation test results are shown in Table 2.

Table 2. Preliminary regression tests

Variables	$rdinput_{i,t}(invest_{i,t})$			$rdoutput_{i,t}(dtrun_{i,t})$		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$rd_put_{i,t}^{^1}$	0.1207***	0.3053***	0.5018***	0.0007**	0.0034***	0.0007**
	(4.1268)	(5.5550)	(2.6099)	(2.3211)	(3.1257)	(2.2431)
$rd_put_{i,t}^{^2}$		-1.5382***			-0.0005***	
		(-4.8006)			(-2.7106)	
$rd_put_{i,t} * threshold$			-0.0201**			-0.0001
			(-2.0654)			(-0.2327)
$capital_{i,t}$	0.0699***	0.0689***	0.0705***	0.0737***	0.0738***	0.0737***
	(5.0280)	(4.9413)	(5.0666)	(5.2112)	(5.2246)	(5.2111)
$ppe_{i,t}$	-0.0053	-0.0058	-0.0054	-0.0051	-0.0053	-0.0051
	(-1.3477)	(-1.4626)	(-1.3725)	(-1.2955)	(-1.3412)	(-1.2961)
$roa_{i,t}$	0.0701***	0.0651***	0.0714***	0.0676***	0.0680***	0.0676***
	(5.2852)	(4.9198)	(5.3902)	(5.0962)	(5.1224)	(5.0965)
$cash_{i,t}$	0.0137**	0.0138**	0.0133**	0.0147**	0.0141**	0.0147**
	(2.1422)	(2.1582)	(2.0844)	(2.2735)	(2.1911)	(2.2739)
$mtb_{i,t}$	0.1307***	0.1349***	0.1264***	0.1450***	0.1438***	0.1450***
	(4.5643)	(4.7400)	(4.4042)	(4.9779)	(4.9627)	(4.9787)
$gdpr_{i,t}$	0.1094***	0.1124***	0.1099***	0.1075***	0.1093***	0.1075***
	(4.4957)	(4.6558)	(4.5219)	(4.3931)	(4.4749)	(4.3910)
$_cons$	-0.0060**	-0.0074***	-0.0060**	-0.0055*	-0.0058**	-0.0055*
	(-2.1364)	(-2.6387)	(-2.1434)	(-1.9324)	(-2.0297)	(-1.9319)
$Cluster(id)$	Yes	Yes	Yes	Yes	Yes	Yes
$Year\ fixed\ effect$	Yes	Yes	Yes	Yes	Yes	Yes
$Observations$	14,140	14,140	14,140	14,140	14,140	14,140
$R-squared$	0.0780	0.0810	0.0790	0.0760	0.0770	0.0760

Notes: *** p < 0.01, ** p < 0.05, and * p < 0.1; T-statistics are in parentheses.

In Table 2, Models 1 and 4 are linear regression models with fixed effects, using clustering robust standard errors to correct for heteroscedasticity and autocorrelation in the panel. The results show a positive relationship between the inputs and outputs of corporate innovation ($rdinput_{i,t}$, $rdoutput_{i,t}$) and group holdings. Models 2 and 5 are quadratic term test models in nonlinear form. The quadratic term coefficients of the input and output of enterprise innovation are negative, and the model may have an inverted U-shaped relationship. We found that although the quadratic term coefficient is significant, the extreme value point of the function may not be in the value domain; hence, it is possible that it is still linear by further calculation. Based on the regression results, Equation (2) was fitted as follows:

$$\widehat{fundgroup}_{i,t} = \widehat{\alpha}_1 + \widehat{\beta}_1 rd_{i,t}^2 + \widehat{\beta}_2 rd_{i,t} + \widehat{\beta}_3 control_variables_{i,t} \quad (8)$$

Subsequently, based on the characteristics of the model and regression results, the turning point of the inverted U-shaped function was calculated using Stata software as follows:

$$(rdinput_{i,t}^*, fundgroup_{i,t}^*) = (0.0853, 0.0054) \quad \hat{I}(0, 0.2183)$$

$$(rdoutput_{i,t}^*, fundgroup_{i,t}^*) = (3.5258, 0.0013) \quad \hat{I}(0.8, 1.783)$$

Function (8) and its turning points are located in the first quadrant and have real economic significance.

Models (3) and (6) in Table 2 show the fork products of the innovation variables and the corresponding threshold variables. The negative fork product of Model (3) and the threshold variable $invest_{i,t}$ indicates that institutional investors are in a state of approval when they choose to hold a company's stock but are influenced by the material investment in innovation. As this investment increases, the risk of innovation increases, and the negative moderating effect is significant. In Model (6) with the threshold variable $dtrun_{i,t}$, the fork product of t is negative, indicating that institutional investors are in a state of recognition of corporate innovation output when they choose to hold the company's stock in a group. This study intends to further explore the innovation results in the regulatory mechanism of the rate of change of hands. The results are negative but not significant, possibly because there is no regulatory effect, or there are multiple directions of moderating effect, but these need confirmation. Thus, from the preliminary regression results, the primary terms of the innovation variables are significantly positive and have some stability, with the inclusion of quadratic and crossover terms. However, the economic relationships involved are not expressed adequately using a linear model and need to be further optimized.

We conclude that the relationship between institutional investor shareholding and firm innovation is a complex function. The fact that the binomial coefficient is significant does not make it possible to assume an inverted U-shaped structure. We need to apply the threshold function for the function area system analysis and determine the reasons for the complex function.

BASELINE MODEL

In this study, the model was tested for threshold effects using Equation (6). The regressions are simulated using the bootstrap self-sampling method, set to bootstrap 300 iterations, and search for 400 sample points to obtain the simulated distribution. Table 3 shows the results of estimation of threshold tests on Models 1 and 2 with material inputs to R&D ($invest_{i,t}$) and excess turnover ($dtrun_{i,t}$) as threshold variables, respectively. The results of single threshold tests for Model 1 led us to a reject the original hypothesis that the model does not have a threshold at the 5% significance level. For Model 2, we reject the original hypothesis that the model does not have a threshold at the 10% marginal significance level. When performing the double threshold test, Model 1 had an F-value of 6.55 and a P-value of 0.3533, with no two thresholds present. Model 2 had an F-value of 17.45 for the double threshold test, corresponding to a P-value of 0.0167, and Model 4 had double thresholds at the 5% significance level.

To provide more intuitive information about the test, the results of interval estimation for the single threshold for Model 1 and the double threshold-setting interval for Model 2 are shown in Figure 4. The results of the test for the single threshold value of innovation input $rdinput_{i,t}$, the single threshold value of innovation output $rdoutput_{i,t}$, and the double threshold value are shown from left to right in Figure 4. The dashed line in the figure indicates the 95% confidence interval for the threshold values in the linear regression test. The curve is the line connecting the search points for each threshold value, and the vertical coordinate corresponding to any point on the curve indicates the likelihood ratio, using that point as the threshold value. The curve intersects the dotted line

at the 95% confidence interval. The narrower the confidence interval, the lesser the influence of unobservable factors; hence, the more accurate the threshold estimate. Figure 4 validates the results reported in Table 3. The single threshold value for innovation input $rdinput_{i,t}$ is significant, and the estimates are more to the right of the graph. The single threshold for innovation output $rdoutput_{i,t}$ is not sufficiently significant. The double threshold for $rdoutput_{i,t}$ performs best, but the direction of adjustment of the threshold variable is complex, which is perhaps why Model 6 in Table 3 is not sufficiently significant. Institutional group holdings are related to the innovation inputs and outputs of listed companies but not in a simple linear manner.

Table 3. Threshold test results

Type of Test	Statistical Quantity	Model 1	Model 2
Single threshold	B	18.8907	-0.1836
	95% confidence interval	[18.0350,18.9513]	[-0.3917, -0.1816]
	F	24.69	9.00
	P	0.0367**	0.1000*
Double thresholds	γ_1	17.8045	-0.1836
	95% confidence interval	[17.7858,17.8228]	[-0.3517, -0.1816]
	γ_2	18.8907	0.0298
	95% confidence interval	[18.7546,18.9513]	[0.0233,0.0306]
	F	6.55	17.45
	P	0.3533	0.0167**
Parameter settings	Number of Bootstrap Sampling	300	300
	Search for Sample Points	400	400
	Observations	14,140	14,140
	n	14	14

Figure 4. Interval estimation for single threshold setting for Model 1 and double threshold setting for Model 2

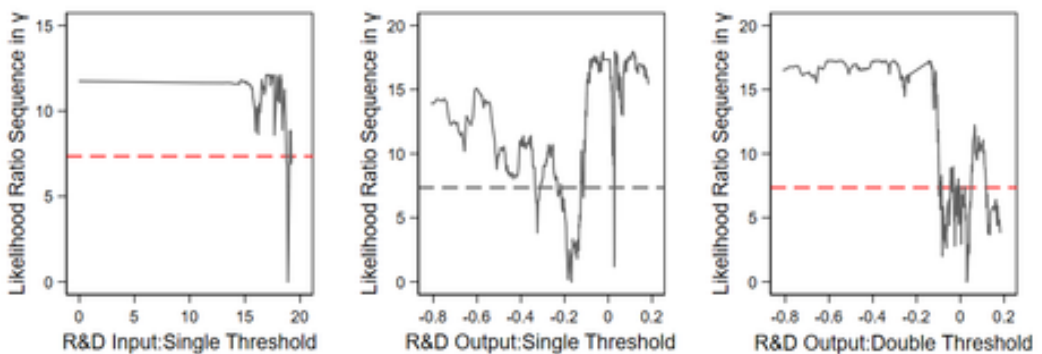


Table 4 presents the threshold regression results for Models 1 and 2. The regression results of Model 1 show that when the material input of innovation is in the low-level range [0.0001, 18.8907], it is called the stage of potential investment in the innovation of listed companies. In this stage, the holdings and acknowledgement of institutional investors increase as companies pay more attention to innovation (impact coefficient = 6.82%). When approaching over-investment in the innovation stage (18.8907, 22.2273], institutional investors' holdings decline as innovation investment continues to rise, and institutional investors feel a potential risk. The relationship between institutional investors' group holdings and firms' innovation inputs presented in Model 1 has a (+, -) signs at a single threshold. We suggest that the effect has two intervals. As firms' innovation inputs translate into innovation outputs, we need to analyze the relationship from an output perspective and focus on the nonlinear relationship between the two under the changing hands ratio.

From the regression results of Model 2, the regression coefficient is negative when entering the reduced position phase with low average excess turnover [-1.7512, -0.1836]. Market investors in this interval are likely to adjust their positions and exit their holdings for various market-inactivity atmospheres or other risk factors. The innovation output at this stage also fails to be recognized by institutional investors and has a negative effect of 0.06%. When entering the moderate average excess turnover stage (-0.1836, 0.0298] (average excess turnover of market investors in the sample in Table 1, -0.1413), market investors in this interval are in normal trading conditions. As the results and outputs of companies' innovations increase, group holdings by institutional investors increase with an impact coefficient of 0.06%. When entering a turbulent phase with a high average excess turnover (0.0298, 1.6767], institutional investors experience a negative impact on their holdings of over-innovative companies because of market sentiment or the operational risks of listed companies. Model 2 shows the relationship between institutional investors' holdings and firms' innovative output with (-, +, -) signs at the double threshold. We suggest that the effect of this relationship has three intervals.

Consequently, technological innovation in listed companies will increase the likelihood of institutional investors' group holdings, with the group holdings concept favoring listed companies labeled "Innovation Active." However, excessive technological innovation in listed companies can reduce institutional investors' likelihood to hold stocks, and the group holdings concept does not favor companies labeled "Innovation Excessive." Hypotheses I and II are tested.

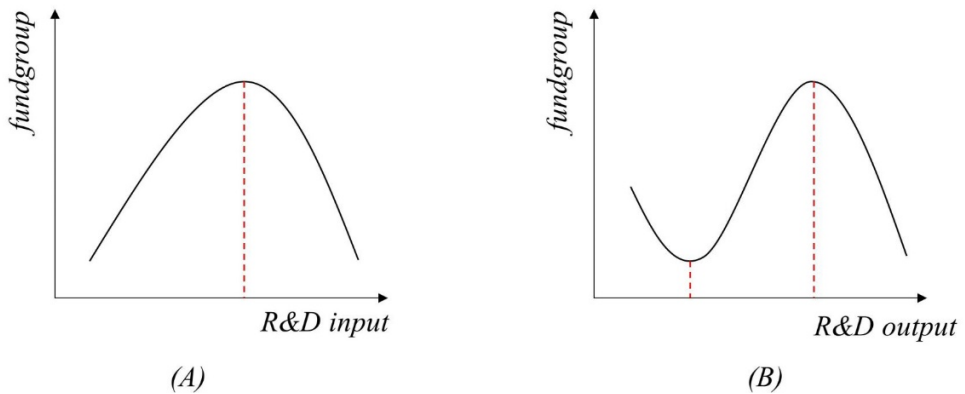
Table 4. Fixed effects regression results

Variables	Model 1	Variables	Model 2
$rdinput_{i,t}(invest_{i,t} \leq \gamma)$	0.0682*** (3.4969)	$rdoutput_{i,t}(dtrun_{i,t} \leq \gamma_1)$	-0.0006** (-2.4175)
$rdinput_{i,t}(invest_{i,t} > \gamma)$	-0.0392** (-2.1740)	$rdoutput_{i,t}(\gamma_1 < dtrun_{i,t} \leq \gamma_2)$	0.0006** (2.6400)
—	—	$rdoutput_{i,t}(dtrun_{i,t} > \gamma_2)$	-0.0008*** (-2.5515)
$capital_{i,t}$	0.0519*** (7.1674)	$capital_{i,t}$	0.0519*** (7.1620)
$ppe_{i,t}$	-0.0046** (-2.0295)	$ppe_{i,t}$	-0.0045** (-1.9781)
$roa_{i,t}$	0.0284*** (4.4537)	$roa_{i,t}$	0.0274*** (4.3220)
$cash_{i,t}$	0.0101*** (3.2148)	$cash_{i,t}$	0.0102*** (3.2542)
$mtb_{i,t}$	0.1585*** (11.9365)	$mtb_{i,t}$	0.1671** (12.5968)
$gdpr_{i,t}$	-0.0754*** (-8.0416)	$gdpr_{i,t}$	-0.0800*** (-8.9900)
$_con$	0.0162*** (14.0366)	$_con$	0.0168*** (15.8031)
Observations	14,140	Observations	14,140
F	40.1580	F	35.8609
R-squared	-0.0518	R-squared	-0.0517

The above threshold regressions remedy the problems with the linear regressions, quadratic regressions, and moderating effects shown in Table 2. The nonlinear relationship between innovation inputs and outputs and institutional investors' group holdings is optimized, and empirical results show that heterogeneity exists between the two in terms of intervals. The regression results are more intuitively reflected in Figure 5, where Figure (A) shows the relationship between firms' technological innovation inputs and institutional investors' holdings. The observed inverted U-shaped relationship between the two is consistent with the inference made in the preliminary study. Figure (B) shows an inverse N-shaped relationship between firms' technological innovation inputs and institutional investors' holdings. The implied multidirectional moderation also explains why the moderation effect is not significant.

The determination of the function area system does not allow us to jump to conclusions, as we need to determine the following issues. First, the two innovation variables $rdinput_{i,t}$ and $rdoutput_{i,t}$ are innovative proxies from different perspectives, but their regressions yield different functions inconsistent with common sense. Second, there is a need to find out why the two are complex functions of each other.

Figure 5. Interval heterogeneity under threshold regression results



STABILITY TEST AND FURTHER RESEARCH

Grouped Regression

To avoid estimation bias in the model specification, this study uses both ordinary least squares (OLS) regression and fixed effects (FE) regression to test the robustness of the above results. The regression results are presented in Table 5, where the sample is grouped using the threshold variables. The estimates of parameters, particularly for the panel regression, were consistent with the baseline regression results of the threshold model, demonstrating robustness.

LAGGED OPERATOR TEST

Table 5. Regression results by group

Variables	$rdinput_{i,t}$		Variables	$rdoutput_{i,t}$	
	OLS	FE		OLS	FE
$invest_{i,t} \leq 18.8907$	0.1893*** (10.0350)	0.0682*** (3.4969)	$dtrun_{i,t} \leq -0.1836$	-0.1080*** (-3.8941)	-0.1204*** (-5.4296)
$invest_{i,t} > 18.8907$	0.0609*** (3.4504)	-0.0392** (-2.1740)	$-0.1836 < dtrun_{i,t} \leq 0.0298$	0.1835*** (9.7382)	0.0636*** (3.5560)
—	—		$dtrun_{i,t} > 0.0298$	-0.1280*** (-4.4465)	-0.0922*** (-4.0186)
$capital_{i,t}$	0.0529*** (6.9066)	0.0519*** (7.1674)	$capital_{i,t}$	0.0522*** (6.8174)	0.0516*** (7.1176)
$ppe_{i,t}$	-0.0144*** (-7.4401)	-0.0046** (-2.0295)	$ppe_{i,t}$	-0.0142*** (-7.3526)	-0.0045** (-1.9803)
$roa_{i,t}$	0.0656*** (9.8022)	0.0284*** (4.4537)	$roa_{i,t}$	0.0621*** (9.2840)	0.0280*** (4.3921)
$cash_{i,t}$	0.0141*** (4.4860)	0.0101*** (3.2148)	$cash_{i,t}$	0.0147*** (4.6937)	0.0102*** (3.2473)
$mtb_{i,t}$	0.0916*** (6.6050)	0.1585*** (11.9365)	$mtb_{i,t}$	0.1051*** (7.5927)	0.1706*** (12.8218)
$gdpr_{i,t}$	0.0123 (1.1785)	-0.0754*** (-8.0416)	$gdpr_{i,t}$	0.0122 (1.1761)	-0.0775*** (-8.2663)
$_cons$	0.0077*** (6.3664)	0.0162*** (14.0366)	$_cons$	0.0075*** (6.1928)	0.0162*** (14.0772)
Observations	14,140	14,140	Observations	14,140	14,140
R-squared	0.0333	0.0239	R-squared	0.0330	0.0247

OLS – ordinary least squares; FE – fixed effects

Both innovation inputs $rdinput_{i,t}$ and innovation outputs $rdoutput_{i,t}$ are measures of technological innovation in firms; however, the results differ when each is subjected to threshold regression. Innovation in firms does not happen overnight and is a cyclical process. The output of innovation is derived from the inputs; therefore, there is a relationship between the two indicators. We lagged innovation inputs $rdinput_{i,t}$ by one period to replace innovation outputs $rdoutput_{i,t}$. The regression results for the lagged data under the threshold variable $dtrun_{i,t}$ are presented in Table 6.

Although innovation inputs are not equal to outputs, their specific results are related to the input-output efficiency of innovation. $L.rdinput_{i,t}$ has a lag operator and a double threshold effect; nevertheless, an inverse N-shape is generated with (-, +, -) sign in three intervals. This indicates that the two innovation indicators are correlated and proves the stability of the model. Both innovation inputs $rdinput_{i,t}$ and innovation outputs $rdoutput_{i,t}$ are inverse N-shape functions that are more complex but are unified.

Table 6. Fixed effects regression results

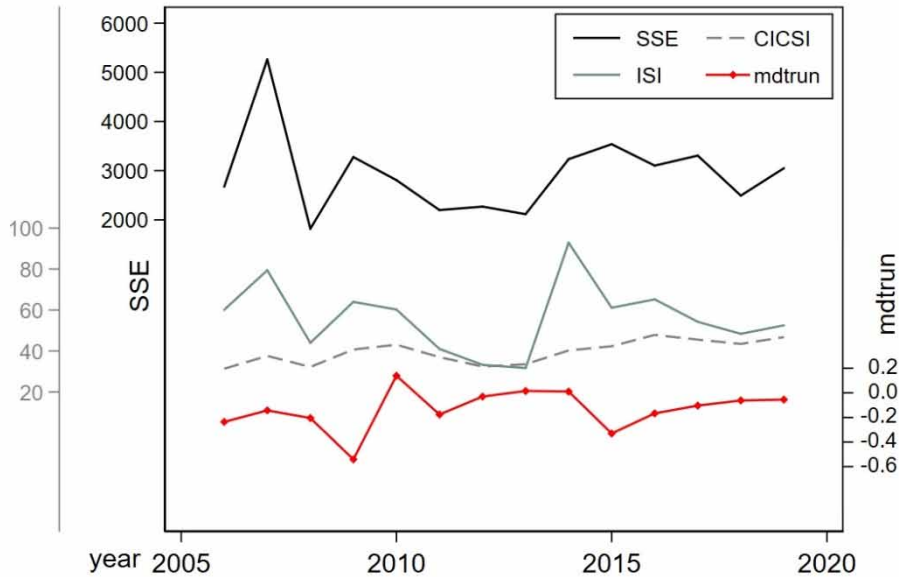
Double Thresholds	Results	Variables	Model 2
γ_1	-0.1353	$L.rdinput_{i,t}(dtrun_{i,t} \leq \gamma_1)$	-0.0784***(-3.6861)
95% confidence interval	[-0.1438, -0.1340]	$L.rdinput_{i,t}(\gamma_1 < dtrun_{i,t} \leq \gamma_2)$	0.0590*** (3.1332)
γ_2	0.1257	$L.rdinput_{i,t}(dtrun_{i,t} > \gamma_2)$	-0.0793***(-2.6853)
95% confidence interval	[0.1128, 0.1277]	$capital_{i,t}$	0.0510*** (6.4926)
F	23.94	$ppe_{i,t}$	-0.0051**(-2.0984)
P	0.0000***	$roa_{i,t}$	0.0246*** (3.7684)
Number of Bootstrap Sampling	300	$cash_{i,t}$	0.0095*** (2.8905)
Search for Sample Points	400	$mtb_{i,t}$	0.1663*** (11.9876)
Observations	13,130	$gdpr_{i,t}$	-0.0813***(-8.0573)
n	13	con	0.0173*** (14.5515)
		F	31.89
		$R-squared$	0.0231

FURTHER RESEARCH

We note that the innovation output $rdoutput_{i,t}$ exhibits an inverse N-shaped function when using the average excess turnover rate as a threshold variable. In related research on equity markets, Baker and Stein (2004) argue that the turnover rate indicator is often used to measure market sentiment, suggesting that it is a good measure of investor sentiment at both the individual stock and market levels. For the Chinese market, the turnover rate is also a core indicator at the market level, as in the CSMAR database A-share market investor sentiment index (ISI) and the China Index of Composite Stock Market Investor Sentiment Index (CICSI). Liu et al. (2020) found significant investor sentiment when studying the Chinese stock market. The investor sentiment toward individual stocks is measured using the turnover rate. He found that investor sentiment explains most market anomalies in the A-share market. From this perspective, the threshold model's regression results can be used to link listed companies' technological innovation and institutional investors' group holdings to sentiment. The market-level and individual stock-level turnover rates were calculated as follows:

- ISI and CICSI. The research idea is to use principal component analysis (PCA) to construct a single indicator into a composite index to reflect market sentiment. In conjunction with related research in China, the CSMAR database publishes two types of market-level sentiment indices.
- Calculation of excess turnover rate of individual stocks in this study. The turnover rate can use the difference between the stock's turnover rate for the current year and the previous year's turnover rate. In this study, we calculate the individual excess stock turnover rate $dtrun_{i,t}$. The stock turnover rate is (average of the fourth quarter monthly turnover rate - average of the third quarter monthly turnover rate). This is because the fourth-quarter data match the end-of-year point-in-time values of the Shanghai Stock Exchange Index (SSE) better. We use $dtrun_{i,t}$ as an indicator of investor sentiment in a market.
- The SSE index, whose sample stocks are all stocks listed on the Shanghai Stock Exchange, includes A shares and B shares. It is the most authoritative composite index of the secondary securities market in China and reflects the volatility and movement of the stock market.
- A line graph of the above indices is shown below:

Figure 6. Time trends in stock indices and turnover rates



The black line in Figure 6 is the SSE index, the red line is the sample mean $mdtrun_{i,t}$ for $dtrun_{i,t}$, the straight line in the gray line is the ISI index, and the dashed line is the CICI index. Individual stock sentiment differs from market sentiment in terms of time trends due to differences in calculation calibration, methodology, and units. However, when combined with the reality of the Chinese stock market, the volatility of the four indices exhibits long-term consistency. There is a relationship between $mdtrun_{i,t}$ of individual stocks and the SSE index. In behavioral finance, trader sentiment is considered an important factor in capital pricing. We further investigate the relationship between firms' innovation output and institutional investors' willingness to hold groups of stocks through the intervention of sentiment factors.

The excess turnover of individual stocks, $dtrun_{i,t}$, is further examined as data that can indicate the sentiment of individual stock investors and may be one of the transmission paths through which corporate innovation affects institutional investors' holdings. Based on the stepwise regression method proposed by Baron and Kenny (1986) to test for mediating effects, this study constructs the following mediating effects model based on the possible paths of influence between institutional investor group holdings, corporate innovation output, and the mediating variable investor sentiment. The model was specified as follows:

$$\begin{aligned} fundgroup_{i,t} &= a_0 + a_1 rdoutput_{i,t} + a_2 control_variables_{i,t} + \delta_i + \eta_t + \varepsilon_{i,t} \\ dtrun_{i,t} &= \beta_0 + \beta_1 rdoutput_{i,t} + \beta_2 control_variables_{i,t} + \delta_i + \eta_t + \varepsilon_{i,t} \\ fundgroup_{i,t} &= \theta_0 + \theta_1 rdoutput_{i,t} + \theta_2 dtrun_{i,t} + \theta_3 control_variables_{i,t} + \delta_i + \eta_t + \varepsilon_{i,t} \end{aligned}$$

Where $dtrun_{i,t}$ is the mediating variable, indicating the investor sentiment toward individual stock i . The results of the first of these three expressions have been reported previously in Model 4 of Table 2, where the coefficient α_1 is 0.0007 ($t=2.3211$) and is statistically significant at the 5% level. Table 7 presents the model estimation results for the second and third expressions in the set of equations—the mediating effects of investor sentiment.

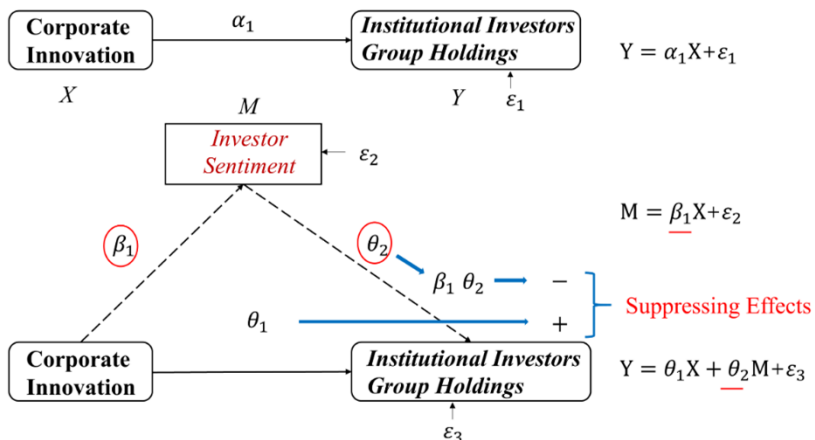
Table 7. Intermediary effects regression results

Variables	Equation 2 $dtrun_{i,t}$	Equation 3 $fundgroup_{i,t}$
$rdoutput_{i,t}$	-0.0024*(-1.7351)	0.0007*** (3.7936)
$dtrun_{i,t}$	—	0.0020** (2.2649)
$capital_{i,t}$	0.0938 (1.4689)	0.0580*** (6.9908)
$ppe_{i,t}$	-0.0351** (-2.3365)	-0.0137*** (-7.4027)
$roa_{i,t}$	0.1888*** (3.4588)	0.0664*** (8.5914)
$cash_{i,t}$	0.0285 (1.0277)	0.0168*** (4.5855)
$mtb_{i,t}$	0.1248 (0.7975)	0.1443*** (8.9426)
$gdpr_{i,t}$	-0.0391 (-0.3025)	0.1166*** (8.5594)
$_{con}$	-0.1475*** (-10.1942)	-0.0039*** (-2.5114)
Observations	14140	14140
F	4.3297	51.2372
R-squared	-0.0518	-0.0517

Notably, the coefficient $\beta_1 = -0.0024$ of the explanatory variable on the mediating variable in Equation 2 is significant and is negative, indicating that investor sentiment inhibits institutional investors from holding the stock. The coefficient θ of the explanatory variable $rdoutput_{i,t}$ and the mediating variable $dtrun_{i,t}$ on the explanatory variable in Equation 3 $\theta_1 = 0.0007$ and $\theta_2 = 0.0020$, with coefficient θ_1 being the result of the effect of the mediating variable being controlled as a latent variable, both of which are statistically significant. The direct share of the specific effect is $|\beta_1 \theta_2|$, θ_1 at 0.0069, and the relative share is $|\beta_1 \theta_2| / (|\beta_1 \theta_2| + |\theta_1|)$ at 0.0068.

The relationship between these three parameters is shown in Figure 7. β_1 , θ_2 and θ_1 have different signs, indicating that there is a suppressing effect of investor sentiment between institutional investors' holdings and listed enterprises' innovation. This figure illustrates several issues. First, enterprises increase their investment into technology innovation, which promotes institutional investors' holdings.

Figure 7. Suppressing effects of investor sentiment



Second, corporate innovation does not positively correlate with investor sentiment, and a negative relationship emerges between innovation and investor holdings. The process of converting a firm's liquid assets as well as its human and material resources into technological power after investment is essentially a process of inward investment and development of intangible assets. This process affects the liquidity of enterprises and increases their operational risk and financial stress, while investor sentiment prevails in the stock market, and some investors are more concerned with the short-term speculative atmosphere. Third, there is a positive correlation between investor sentiment and institutional investor group holdings. When stocks are favored by investors, generally structural, the market is generally positive, and institutional investors will hold them. Fourth, investor sentiment mediates the positive correlation between increased investment in innovation and institutional investor group holdings. However, the financing effect of innovation is influenced by the suppressing effect of overall investor sentiment. Fifth, from the specific data, we note that investor sentiment can play a masking role. Nevertheless, it does not account for a high proportion, which also indicates that institutional investors have their own strategies and judgment criteria when holding stocks in groups. Therefore, there is a negative transmission mechanism between institutional investors' holdings and market sentiment for listed companies that are labeled as "Innovation Excessive" or have unusual investments in on-balance sheet intangible assets in their financial disclosures. Hypothesis III is tested. Combined with the fact that the moderating effect function was not significant in the preliminary study, we believe that the complexity of the function is likely to be related to emotional factors.

CONCLUSIONS AND DISCUSSION

Innovation is an important way for enterprises to ensure their leading position in the market and is an inexhaustible driving force for sustainable macroeconomic development. From the perspective of the enterprises themselves, engaging in technological innovation activities is characterized by long-term investment and uncertainty of returns. This makes it necessary for the management of enterprises to consider multiple interests when making innovation decisions. This study investigates the impact of corporate innovation activities on institutional investors' group holdings of a company's stocks by constructing a complex network using data on listed companies in China's A-share market from 2006 to 2019. The results of grouped regression show that there was no change in the correlation functions of the two variables. Additionally, we lagged innovation inputs according to the R&D cycle and found that the regression results were similar to those for innovation output. The study found a significant correlation between corporate technological innovation activities and institutional investors' group holdings and that this correlation is not a simple linear one. The regression results of the threshold model show an inverted U-shaped relationship between investment in technology and innovation and institutional investors' group holdings. An increase in corporate investment in innovation can provide incentive for institutional investors to hold. However, after peaking, the proportion of institutional investors' holdings decreases as more innovation is invested in them. The relationship between firms' innovation output and institutional investors' holdings is clearly more complex, with an inverse N-shaped relationship when investor sentiment is the threshold variable. When investor sentiment is low, innovation output is negatively correlated with institutional investor holdings, and innovation indicators struggle to reverse the negative impact of market sentiment. When investor sentiment is in an intermediate region, the higher the innovation output, the higher is the proportion of external institutional investors' group holdings, which has a positive effect. When investor sentiment is in an intermediate region, the higher the innovation output, the higher is the proportion of external institutional investors' fund holdings, which has a positive effect. As market sentiment rises further, the overall turnover rate of investors is high, and they frequently begin to "pass the parcel"—when institutional investors sense the market risk factor and choose to exit, they are most likely to complete the arbitrage process. In short, the concept of institutional investors'

group holdings is more favorable to listed companies labeled “Innovation Active,” and they are not interested in listed companies labeled “Innovation Excessive.”

Therefore, this paper puts forward the following suggestions:

- (1) The government should strengthen its support for technological innovations. At this stage, in particular, the scale of investment in the R&D of enterprises in China’s strategic emerging industries is large, and the overall level of innovation is higher than that of traditional industries. Some enterprises have not yet formed the driving force of technology-driven economic growth and still require capital incubation. Additionally, China’s financial market structure is dominated by bank credit. The relevant departments should actively promote a market-based financing channel that combines securities, banks, funds, and insurance. They should guide financial institutions to actively participate in the scientific and technological innovation activities of enterprises to provide high-tech enterprises with a stable and rational financing channel in the stock market.
- (2) Enterprises should focus on R&D activities and related information disclosure. The research in this study shows that although innovation activities can promote institutional investors’ holding ratio, the coefficient is low, and the actual pulling effect is insufficient. After peaking, excessive innovation investment affected institutional investors’ willingness to invest negatively. Investors in the securities market, as external equity holders in enterprises, do not have sufficient information on corporate R&D disclosure. For enterprises in strategic emerging industries, the intensity of R&D activities is considerably high. Enterprises should properly disclose the progress of their R&D projects and related long-term strategies to outsiders without revealing trade secrets to mitigate the negative impact of innovation spending on investor sentiment by reducing the information asymmetry between investors and corporate authorities.
- (3) Relevant market regulators should improve supervision and risk control. On the one hand, some companies speculate on this concept in the field of high-tech innovation. Regression analyses revealed that higher innovation investment make institutions in the capital market aware of the strategic or operational risk of the companies and choose to exit. Effective monitoring and management are the only ways to identify the most innovative companies that pay attention to doing solid work. It is also important to screen fraudulent companies as perceived by the capital market. On the other hand, it is important to recognize the suppressing effect of investors in the market as a whole and guide rational investment correctly. This will enable the capital market to better serve value investment and attach importance to long-term investment so that it can play the role of institutional investors better in stabilizing the market and realizing the virtuous cycle of the financial market to promote the real economy.

This study has certain shortcomings and perspectives. The study investigates corporate innovation and external equity financing without considering the life-cycle theory of the firm. In fact, listed companies are at different stages of their life cycles and are likely to differ in terms of innovation investment and share structure.

Further, this study did not consider the heterogeneity of firms or corporate governance. For example, there may be differences in the relationship between financing structure and the level of innovation between state-owned and private firms, as well as between large-, small-, and medium-sized firms. There may also be differences in their preferences for financing and the intensity of investment in R&D.

This study did not consider the spillover effects of increased financing on firms’ innovation activities. Receiving more financing inputs as a result of their innovation inputs will provide financial incentives for firms to invest further in innovation, thus generating a more complex model structure.

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ENDNOTES

- ¹ Global database improved by celyasi data information Co., Ltd. (CEIC)
- ² The concept of “group holdings” is a real and highly popular operation in the Chinese stock market. From a data technology perspective, as institutional investors are related to each other because they hold the same stock, to better measure “grouping,” network techniques and graph clustering can be used. Therefore, it is worth exploring whether the inputs and outputs related to corporate innovation can generate interest in institutional investors to group together, thus translating national advocacy into corporate action and from corporate behavior to financial market linkages.
- ³ China Stock Market & Accounting Research Database is a research-oriented and accurate data-base in the field of economy and finance developed by Shenzhen Sigma Data Technology Co., Ltd. from the needs of academic research and combining with the actual situation of China.
- ⁴ The Wind Economic Database pairs over 1.3 million macroeconomic and industry time series with powerful graphics and data analysis tools to give financial professionals the most comprehensive insights into China's economy.
- ⁵ According to the “ALMANAC OF CHINA'S FINANCE AND BANKING,” the total number of listed companies in China in 2006 was 1,434, with 563,778 million shares in circulation.
- ⁶ Special treatment: refers to the abnormal financial or other conditions of a listed company.