# Is there a spillover effect of stock liquidity on the Total Factor Productivity (TFP) of non-listed firms? Evidence from China

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**Abstract:** Can the stock market promote the TFP growth of non-listed enterprises through the indirect mechanism of non-financing? Based on the perspective of stock liquidity, this paper examines this issue. The results show that the TFP growth of non-listed enterprises (especially those with backward productivity) is subject to the non-collaborative innovation of their industries, and the increase of stock liquidity of listed companies can inhibit the negative impact of non-collaborative innovation by promoting the learning of private information and improving the level of corporate governance of non-listed enterprises in the same industry, thus promoting the TFP growth of non-listed enterprises. This paper finds that an active capital market serves as a financial public good, indirectly generating positive externalities on the TFP growth of non-listed enterprises.

**Keyword:** Stock liquidity; Non-collaborative innovation; Information asymmetry; Financing constraints; Corporate governance; Total factor productivity;

# 1.Introduction

Compared to the commercial banking system, the stock market offers advantages in terms of risk sharing and the promotion of emerging industries, making it more conducive to the growth of total factor productivity (TFP) in listed enterprises (Allen et al., 2024; Bennett et al., 2020; Heil, 2018; Wurgler, 2000). The research reveals that the informational effect of financial asset prices influences corporate decision-making (Bond et al., 2012; Bond et al., 2010; Dow and Gorton, 1997; Goldstein, 2023). Empirical research confirms that the informational effect of financial asset prices indeed influences corporate investment decisions (Bakke and Whited, 2010; Chen et al., 2007; Dieler et al., 2023; Durnev et al., 2004; Edmans et al., 2017; Foucault and

Frésard, 2012, 2014; Jang et al., 2022), as well as other corporate decisions (Ben-Nasr and Alshwer, 2016; De Cesari and Huang-Meier, 2015; Ferreira et al., 2011; Ferreira and Laux, 2007; Frésard, 2012; Gorton et al., 2017; Jin and Myers, 2006; Luo, 2005; Subrahmanyam and Titman, 1999). Regarding the direct influence of financial markets on enterprise productivity, David et al. (2016) find that financial markets have a limited impact on the productivity of listed companies from an investment perspective. Bennett et al. (2020) provide direct evidence that financial markets enhance the productivity of listed companies. However, it is important to note that economic development relies not only on the TFP growth of thousands of listed companies but also, and perhaps more importantly, on the TFP growth of millions of non-listed firms. For example, as of the end of 2022, the number of listed companies in China's A-share market is only slightly over five thousand, while the total number of market players reaches 169 million. Unfortunately, only listed companies leverage the direct financing services of the stock market, while numerous non-listed firms are excluded and do not seem to benefit from the influences of the stock market. This raises an important question: Can the stock market promote TFP growth of non-listed firms through indirect mechanisms other than financing, thereby contributing to economic development?

On one hand, literature indicates that stock liquidity plays a crucial role in resource allocation within the stock market. It is closely tied to market informational efficiency, equity financing costs for listed companies, and corporate governance. When stock liquidity of listed companies increases, the informational efficiency of stock prices improves (Holmstrom and Tirole, 1993; Kerr et al., 2020), equity financing costs decrease (Amihud et al., 2023; Amihud and Mendelson, 2012; Lipson and Mortal, 2009), and corporate governance improves (Bharath et al., 2013; Chen et al., 2015; Edmans, 2009; Edmans et al., 2013). These impacts of stock liquidity may be transmitted within the industry chain, leading to a positive spillover effect on the TFP of related non-listed companies. This implies that a liquid secondary stock market could act as a financial public good, thereby indirectly exerting positive externalities on the TFP growth of non-listed firms.

On the other hand, enterprise productivity growth depends on breakthroughs in emerging general-purpose technologies. The extent of productivity growth is influenced by the level of complementary and synergistic innovation within the industry (Acemoglu et al., 2024). Complementary innovation activities required by an industry are widely dispersed across the economy. Moreover, these activities inherently face uncertainties and information asymmetry, making it exceedingly difficult to incentivize and coordinate innovation in sectors applying emerging general-purpose technologies (Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1996).

Based on the above findings, this paper examines how improvements in the stock liquidity of listed companies stimulate TFP growth in non-listed firms by mitigating the negative impacts of innovation imbalance. Stock liquidity improvements of listed firms may mitigate the negative effects of innovation imbalance on firm TFP by facilitating learning from private information within the same industry (information mechanism), alleviating financing constraints faced by non-listed firms (financing mechanism), and improving corporate governance levels of non-listed firms (governance mechanism), thereby promoting TFP growth in non-listed firms.

Based on several developed hypotheses, a series of empirical studies are conducted. First, we construct a fixed-effects panel data model to investigate the impact of stock liquidity of listed companies on the TFP of non-listed firms within the same industry. The results indicate that, ceteris paribus, an increase (or decrease) in the stock liquidity of listed companies results in a corresponding increase (or decrease) in the TFP of non-listed firms within the same industry. This suggests that stock liquidity has a significant spillover effect on the TFP of non-listed firms in the same industry. The findings pass a series of robustness checks, including substituting explanatory variables, changing dependent variables, conducting regression analyses by ownership type, regional grouping of non-listed firms, and dividing periods before and after the 2008 financial crisis. Second, we build a fixed-effects moderated panel data model to examine the mechanisms through which stock liquidity of listed companies affects the TFP of non-listed firms. The results of mechanism testing indicate that the increase in stock liquidity of listed companies in the same industry promotes TFP growth of non-listed firms by mitigating the negative effects of innovation imbalance. TFP growth of non-listed firms mainly originates from firms with lower productivity, which echoes the findings of Andrews et al. (2016). Further analysis shows that the information and governance mechanisms are significant, whereas the financing mechanism is not.

This paper makes three main contributions: First, it extends research on the impact of financial markets on economic development. Early research explored how the informational content of financial asset prices influences corporate decisions (Bond et al., 2012; Bond et al., 2010; Dow and Gorton, 1997; Hayek, 1945). Empirical findings confirm that the informational effect of financial asset prices affects corporate investment (Bakke and Whited, 2010; Chen et al., 2007; Dieler et al., 2023; Durnev et al., 2004; Edmans et al., 2017; Foucault and Frésard, 2012, 2014; Jang et al., 2022) and other corporate decisions (Ben-Nasr and Alshwer, 2016; De Cesari and Huang-Meier, 2015; Ferreira et al., 2011; Ferreira and Laux, 2007; Frésard, 2012; Gorton et al., 2017; Jin and Myers, 2006; Luo, 2005; Subrahmanyam and Titman, 1999). More recent studies focus on the direct impacts of financial markets on economic development. David et al. (2016) find a limited impact of the financial market on the productivity of listed firms from the investment angle, whereas Bennett et al. (2020) provide direct evidence of financial markets enhancing listed firms' productivity. This paper, from the perspective of non-listed firms, provides theoretical and empirical support for the role of financial markets in economic development. Second, it broadens research on the impact of stock liquidity on corporate operations. Existing research finds that increased stock liquidity in listed companies enhances informational efficiency of stock prices (Holmstrom and Tirole, 1993; Kerr et al., 2020), reduces equity financing costs (Amihud et al., 2023; Amihud and Mendelson, 2012; Lipson and Mortal, 2009), and improves corporate governance (Bharath et al., 2013; Chen et al., 2015; Edmans, 2009; Edmans et al., 2013). This paper extends studies on how stock liquidity affects corporate operations by demonstrating that stock liquidity enhances TFP through informational and governance mechanisms. Third, scholars point out that productivity improvements often lag behind breakthroughs in relevant technologies, as industries typically take a long time to master these new technologies (David, 1990). Bresnahan and Trajtenberg (1995) and Helpman and Trajtenberg (1996) elucidate the formation mechanisms of innovation imbalance, emphasizing the distributed nature of complementary innovation activities across the economy and the inherent uncertainties and information asymmetry in corporate innovation activities, making it difficult to incentivize and coordinate these activities. Brynjolfsson et al. (2021) observe that productivity gains from artificial intelligence and other digital technologies follow a J-curve, as complementary investments and technologies require time to develop. This paper explores how innovation imbalance within the same industry affects the productivity of non-listed firms, expanding research on the impact of innovation imbalance on enterprise productivity.

The remainder of the paper is structured as follows: Section 2 presents the hypotheses, Section 3 outlines the empirical research design, Section 4 discusses the empirical results, Section 5 provides mechanism analysis, and Section 6 concludes.

# 2.Hypotheses Development

### (1) Industrial Innovation imbalance and its Suppressive Effect on Firms' TFP Growth

Firm productivity often experiences significant leaps due to major breakthroughs in emerging general-purpose technologies. These technologies are widely and deeply applied across industries. Bresnahan and Trajtenberg (1995) and Helpman and Trajtenberg (1996) highlight the characteristics of emerging general-purpose technologies, such as universality, potential to drive advancements in related complementary technologies, and innovation synergies. These emerging general-purpose technologies enable industries or firms to achieve increasing returns to scale, thereby realizing substantial productivity leaps. However, for most specific industries or firms, an emerging general-purpose technology acts as an "enabling technology," creating new potential opportunities for production technology advancement rather than providing a complete final solution. Therefore, the extent to which an industry exploits the productivity growth potential of emerging general-purpose technologies depends on how firms within that industry engage in complementary innovation. For instance, breakthroughs in computer science open up vast potential applications for the personal computer industry. However, the design and production of personal computer end-products still rely on the synergistic innovation and deep integration of complementary technologies such as semiconductor technology, display technology, internet technology, and computer software technology.

In this process, if certain complementary technologies within the industry lag significantly in their research and development (referred to as industry innovation imbalance, where the greater the disparity in innovation levels among related complementary technologies within the industry, the higher the degree of industry innovation imbalance), this can severely constrain the productivity growth of the entire industry chain, resulting in a "bottleneck effect" or "growth bottleneck." This results in actual productivity growth falling significantly below the potential growth opportunities offered by emerging general-purpose technologies (Acemoglu et al., 2024). Within the example of the personal computer industry, if semiconductor technology development lags significantly behind other complementary technologies, it creates a computational power constraint, limiting the commercial application of innovative technologies such as high-definition displays and advanced computer software in personal computers. The lag in semiconductor technology not only inhibits productivity improvement in the personal computer industry by imposing computational power constraints but also impedes the commercial application of other complementary technological innovations. This, in turn, weakens innovation incentives in other segments of the industry. Hence, industry innovation imbalance significantly suppresses TFP growth within firms in the industry.

### (2) Factors Leading to Industry Innovation imbalance

Current research indicates that industry innovation imbalance based on emerging technologies has been a widespread and unavoidable phenomenon throughout human social development history. For instance, David (1990) examines the process of industrial electrification in the United States and finds that productivity growth from emerging general-purpose technologies often lags significantly behind its potential growth opportunities. Andrews et al. (2016) observe that although leading firms' productivity continues to grow steadily, the decline in overall economic productivity is notably correlated with the poor productivity performance of non-frontier (non-leading) firms across different industries and countries. Brynjolfsson et al. (2021) point out that due to the necessity for complementary investments and technologies to develop over time, the productivity gains from AI and other digital technologies follow a J-curve. Acemoglu et al. (2024) further elucidate the theoretical mechanism by which the uneven distribution of innovation activities related to emerging general-purpose technologies across sectors leads to slow productivity growth in the economy, providing ample empirical evidence from the background of U.S. communication technology development on the slow productivity growth.

One critical factor contributing to industry innovation imbalance is the presence of information asymmetry, which hinders the coordination of complementary innovation activities. Bresnahan and Trajtenberg (1995) and Helpman and Trajtenberg (1996) provided detailed analyses of the formation mechanisms of innovation imbalance. Given that complementary innovative activities required by an industry are widely dispersed across the entire economy and corporate innovation activities inherently face uncertainty and information asymmetry issues, incentivizing and coordinating innovation activities across various sectors within that industry become highly challenging. Particularly, since companies within an industry have different "distances" on the technological development path for applying the new emerging general-purpose technology, industry synergistic innovation necessarily exhibits discontinuity and temporal characteristics (i.e., companies farther from the frontier will inevitably lag behind those closer to it in terms of technological development). Fully exploiting the growth opportunities from industry emerging general-purpose technology relies on the complementary synergistic innovation of all firms along the technological development paths in the industry. Therefore, most industries usually struggle to fully exploit the growth opportunities from emerging general-purpose technologies in a short period. This is especially true for firms with relatively lagging productivity, which often operate far from the technological frontier of their industry. These firms face high uncertainty and information asymmetry, resulting in weaker incentives for synergistic innovation. The innovation lag of these lagging firms further exacerbates industry innovation imbalance, thereby suppressing the productivity growth of these firms and other related firms.

Furthermore, the problem of financing constraints and agency issues could also be critical factors leading to industry innovation imbalance. On the one hand, firms' innovation activities inherently face future uncertainties and information asymmetry with investors and creditors. As a result, these firms face varying degrees of financing constraints. Financing constraints can cause firms' investment decisions to deviate from the optimal path, resulting in underinvestment and lagging innovation activities (Miller and Rock, 1985; Moshirian et al., 2021; Myers and Majluf, 1984). In particular, firms with relatively lagging productivity are more likely to face financing constraints, this issue may inhibit their innovative investment activities, further intensifying industry innovation imbalance. On the other hand, uncertainties and information asymmetry can also lead to serious agency problems. In modern enterprises, ownership and control rights are usually separated. Since managers have an informational advantage over owners and the cost of owners supervising managers is high, managers are sufficiently incentivized to maximize private benefits rather than shareholder value through practices like embezzlement and related-party transactions (Jensen and Meckling, 1976; Shleifer and Vishny, 1997). This further leads to resource misallocation and inhibits the firm's pursuit of frontier innovation activities. This is especially pronounced for firms with relatively lagging productivity, as their managers face relatively low opportunity costs in terms of industry reputation.

### (3) How Stock Liquidity Affects Firms' TFP Growth by Mitigating Industry Innovation imbalance

A substantial body of literature shows that stock liquidity plays an essential role in capital market resource allocation and corporate governance. First, stock liquidity positively impacts stock market information integration and price discovery. Improved stock liquidity helps reduce the price impact of informed traders' orders, thereby slowing the revelation of private information through stock price changes. This leads to more optimal order sizes for informed trading, thereby increasing the expected profits of informed trading and enhancing the incentives for private information collection, ultimately improving stock market information efficiency (Holmstrom and Tirole, 1993; Kerr et al., 2020; Kyle, 1985; Sadka, 2006). Second, stock liquidity significantly influences asset pricing. When stock liquidity is low, investors incur implicit costs, such as trading at disadvantageous prices or delaying trades. These costs necessitate higher expected returns to compensate for the implicit transaction costs associated with illiquid stocks. Hence, improved stock liquidity leads to lower expected stock returns (Amihud et al., 2015a, b; Amihud and Mendelson, 1986; Datar et al., 1998; Hasbrouck, 2009; Longstaff, 1995; Silber, 1991), and consequently, lower equity financing costs for listed firms (Amihud et al., 2023; Amihud and Mendelson, 2012; Diamond and Verrecchia, 1991; Lipson and Mortal, 2009; Ng, 2011; Sadka, 2011). Third, increased stock liquidity enhances corporate governance by lowering transaction costs, thereby increasing the risk of listed companies being taken over in the secondary market (Kyle and Vila, 1991). If managers underperform, leading to a decline in the company's market value, the risk of an external takeover increases. To avoid dismissal after a takeover, managers are incentivized to improve company performance when stock liquidity improves (Maug, 1998). Additionally, if managers engage in "short-sighted" decision-making, major shareholders who are unable to directly intervene can "vote with their feet" by selling their stocks in the secondary market. This causes stock price changes to reflect managerial short-sighted behavior as punishment (e.g., loss of stock-price-linked income and industry reputation). Improved stock liquidity lowers the costs of secondary market transactions, enhancing the credibility of shareholders' "exit" threats. This, in turn, constrains managerial short-sighted behavior (Bharath et al., 2013; Chen et al., 2015; Edmans, 2009; Edmans et al., 2013). Finally, improved stock liquidity can enhance stock market information efficiency, making managerial compensation more sensitive to stock price changes. This optimizes compensation incentives and lowers agency costs (Fang et al., 2009; Jayaraman and Milbourn, 2011).

As these effects of stock liquidity on listed companies propagate through the supply chain, increases in stock liquidity may mitigate the negative impacts of industry innovation imbalance on the TFP growth of non-listed firms, subsequently enhancing their TFP. First, increased stock liquidity enhances the informativeness of stock prices. Listed companies often play a central role in industry resource allocation, and their private information is closely related to the industry's future prospects (Acemoglu et al., 2024). Firms with more severe information asymmetry within an industry are less likely to undertake innovation activities due to the uncertainty of future opportunities, thus lagging in technological advancement. These firms' ability to catch up technologically relies more heavily on information collection and investment decisions. By learning about private information embedded in stock prices to optimize key decisions on technology development (Bennett et al., 2020; Luo, 2005), non-listed firms can effectively mitigate the negative impacts of uncertainty and information asymmetry on complementary innovation activities (referred to as the information mechanism). Second, improved stock liquidity reduces the equity financing costs of listed firms, preventing them from being diverted from their optimal investment path due to financing constraints (which can inhibit scale expansion) and aiding in their expansion (Amihud et al., 2023). The technological catch-up of productivity-lagging firms within an industry is more constrained by financing issues. The procurement of intermediate products and service demand associated with the scale expansion of listed companies can propagate through the supply chain to upstream and downstream non-listed firms, improving their cash flow and alleviating their underinvestment in innovation and other activities due to financing constraints (referred to as the financing mechanism). Third, improved stock liquidity strengthens the corporate governance of listed firms, alleviating problems such as embezzlement and related-party transactions due to principal-agent conflicts. Such issues divert firms from the goal of maximizing shareholder value, weaken their incentives to engage in market competition and complementary innovation activities, and exacerbate industry innovation imbalance. As listed companies' related-party transactions often involve non-listed firms within the same supply chain, enhanced stock liquidity indirectly curtails related-party transactions of non-listed firms. This reduces their agency costs, strengthens their competitive and innovation incentives, and ultimately enhances TFP growth (referred to as the governance mechanism). Therefore, we propose the following hypotheses:

Hypothesis I: All else being equal, increases (decreases) in the stock liquidity of listed firms lead to increases (decreases) in the TFP of non-listed firms within the same industry.

Hypothesis II: Increases (decreases) in the stock liquidity of listed firms mitigate (exacerbate) the negative impacts of innovation imbalance, leading to increases (decreases) in the TFP of non-listed firms within the same industry.

Hypothesis IIA: Increases (decreases) in the stock liquidity of listed firms mitigate (exacerbate) the negative impacts of innovation imbalance via the information mechanism, leading to increases (decreases) in the TFP of non-listed firms within the same industry.

Hypothesis IIB: Increases (decreases) in the stock liquidity of listed firms mitigate (exacerbate) the negative impacts of innovation imbalance via the financing mechanism, leading to increases (decreases) in the TFP of non-listed firms within the same industry.

Hypothesis IIC: Increases (decreases) in the stock liquidity of listed firms mitigate (exacerbate) the negative impacts of innovation imbalance via the governance mechanism, leading to increases (decreases) in the TFP of non-listed firms within the same industry.

# 3. Empirical Research Design

**(1) Main Variables**

**TFP (Total Factor Productivity):** Total factor productivity (TFP) represents the growth in real output that exceeds the growth in inputs such as labor and capital (Solow, 1956). It is the portion of output not explained by the inputs used in production (Solow, 1957).Thus, TFP reflects the overall productivity level of the enterprise. The production function of the enterprise is typically assumed to follow the logarithmic Cobb-Douglas production function:

$$y_{i,t} = \alpha + \beta l_{i,t} + \gamma k_{i,t} + \omega_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ represents the natural logarithm of output or value added of enterprise $i$ in year $t, l_{i,t}$ denotes the natural logarithm of labor input of enterprise $i$ in year $t, k_{i,t}$ signifies the natural logarithm of capital stock of enterprise $i$ in year $t, \omega_{i,t}$ stands for the unobservable productivity shock to enterprise $i$ in year $t, \varepsilon_{i,t}$ is the random error term;

$\alpha$ is the intercept term,$\beta$ and $\gamma$ represent the output elasticities of labor and capital, respectively. The term $(\alpha + \omega_{i,t})$ represents the enterprise's TFP. Notably, the residual term can be further decomposed into$(\omega_{i,t} + \varepsilon_{i,t})$ and $\omega_{i,t}$ is assumed to follow a first-order Markov process:

$$\omega_{i,t} = E\left(\omega_{i,t} \middle| \Omega_{i,t-1}\right) + \mu_{i,t}, \tag{2}$$

is instrumental in addressing the potential simultaneity bias during productivity estimation (Hulten, 1978; Marschak and Andrews, 1944). $\Omega_{i,t-1}$represents the information set available for firm $i$ in year $t$ for making production decisions, and $\mu_{i,t}$ denotes independent random productivity shocks.

This paper employs several widely-used methods to estimate the TFP of non-listed firms, including the OP method by Olley and Pakes (1996), the LP method by

Levinsohn and Petrin (2003), and the GMM method by Wooldridge (2009), resulting in the TFP indicators OP, LP, and WRDG respectively. Additionally, Ackerberg et al. (2015) raised concerns that the OP and LP methods may overlook the adjustment costs associated with factor inputs in response to productivity shocks, potentially leading to severe multicollinearity in the first-step estimates. To address this, we utilize the Ackerberg et al. (2015) adjustment (ACF method) to correct the OP and LP indicators. The adjusted indicators, OPacf and LPacf, are used for robustness checks.

**Stock Liquidity:** Stock liquidity is defined as the degree to which the stock market price remains unaffected by stock trade orders. It reflects the additional costs incurred (relative to the current market price) to immediately complete a given volume of stock transactions. Following the method proposed by Amihud (2002), we construct the illiquidity index $ILLIQ$ as an inverse measure of stock liquidity:

$$ILLIQ_{i,t} = \frac{1}{D_{i,t}} \sum_{n=1}^{D_{i,t}} \frac{|r_{i,t,d}|}{VOLD_{i,t,d}}, \quad (3)$$

where $ILLIQ_{i,t}$ denotes the stock illiquidity of listed company $i$ in year $t$; $|r_{i,t,d}|$represents the absolute value of the return of listed company $i$ on day $d$ of year $t$; $VOLD_{i,t,d}$ represents the trading volume of listed company $i$ on day $d$ of year $t$; and $D_{i,t}$ represents the total number of trading days for listed company $i$ in year $t$. As defined in equation (3), the illiquidity index $ILLIQ_{i,t}$ reflects the average impact of one unit of trading volume on daily stock returns over the course of a year. Clearly, this measure is negatively related to stock liquidity; hence, a higher value of $ILLIQ_{i,t}$ indicates lower stock liquidity. We calculate the average $ILLIQ_{i,t}$ for all listed companies within the same industry as the non-listed firm, denoted as $ILLIQ\_Mean_{j,t}$, to measure the stock illiquidity level of the industry $j$ of year $t$. Additionally, to further address potential endogeneity issues, we use a dummy variable $Liquidity_{j,t}$ to measure the stock illiquidity level of the industry $j$ of year $t$ in which the non-listed firm operates. If the value of $ILLIQ\_Mean_{j,t}$ for non-listed firms is in the upper 50% of the sample for the same year, $Liquidity_{j,t}$ is set to 1, indicating higher stock liquidity in the industry. Otherwise, it is set to 0, indicating lower stock liquidity.

**Industry Innovation imbalance:** Industry innovation imbalance is defined as the extent to which the productivity improvements of firms within an industry are inconsistent. Based on this definition, we measure the degree of industry innovation imbalance using statistical indices that capture productivity dispersion. This study estimates industry innovation imbalance using two methods:

1. The standard deviations of TFP for all firms within an industry $j$ of year $t$, denoted as $SDOP_{j,t}$ (standard deviation of OP), $SDLP_{j,t}$ (standard deviation of LP), and $SDWRDG_{j,t}$ (standard deviation of WRDG), reflect the degree of innovation imbalance within the industry during the same period;
2. The difference between a firm's TFP and the 90th percentile of the industry $j$ of year $t$, denoted as $QDOP_{j,t}$ (quantile difference of OP), $QDLP_{j,t}$ (quantile difference of LP), and $QDWRDG_{j,t}$ (quantile difference of WRDG), reflects the gap between a firm's TFP and the industry's frontier level in the same period.

A larger standard deviation or quantile difference in TFP indicates a higher dispersion in productivity among firms within the industry. This implies greater inconsistency in productivity improvements.

**Control Variables:** The control variables used in this study include:

1. **Firm Size ($Size_{i,t}$):** The natural logarithm of the total assets of non-listed firms $i$ of year $t$. Firm size is an important factor affecting both productivity and stock liquidity.
2. **Financial Leverage ($Leverage_{i,t}$):** The ratio of total liabilities to total assets of non-listed firms $i$ of year $t$. Capital structure can impact both investment decisions and market value.
3. **Growth ($Growth_{i,t}$):** The year-over-year growth rate of operating revenue of non-listed firms $i$ of year $t$. Firms at different growth stages exhibit different characteristics in productivity and stock liquidity.
4. **Capital Intensity ($CapInt_{i,t}$):** The ratio of net fixed assets to the number of employees of non-listed firms $i$ of year $t$. Differences in factor input combinations can impact both productivity and investor preferences.
5. **New Investment ($IA_{i,t}$):** The ratio of new investment to total assets of non-listed firms $i$ of year $t$. Investment decisions may significantly impact short-term productivity and market valuation.
6. **Financing Constraint Index ($SA_{i,t}$):**

$$SA = (-0.737) \times Size + 0.043 \times Size^2 - 0.04 \times Age$$

Proposed by Hadlock and Pierce (2010), the SA index uses firm age as a key variable. Higher SA values indicate lower financing constraints.

The definitions of the main variables used in empirical research are listed in Table 1.

**Table 1: Definition of the main variables**

| Variable | Name | Definition |
|---|---|---|
| $OP$ | Total Factor Productivity | TFP of non-listed enterprises estimated by OP method |
| $LP$ | | TFP of non-listed enterprises estimated by LP method |
| $WRDG$ | | TFP of non-listed enterprises estimated by GMM method |
| $OPacf$ | | by OP method and ACF adjustment |
| $LPacf$ | | by LP method and ACF adjustment |
| $ILLIQ\_Mean$ | Stock illiquidity | The average of the illiquidity index of all listed companies in the industry to which the non-listed company belongs$ILLIQ$ |
| $Liquidity$ | Stock Liquidity | Dummy variable, which takes the value of 1 when $ILLIQ_Mean$the value of non-listed enterprises is in the bottom 50% in the sample of the same year, otherwise it takes the value of 0 |
| $SDOP$ | Non-collaborative innovation | The standard deviation of all enterprise indicators in the industry to which non-listed enterprises belong$OP$ |
| $SDLP$ | | The standard deviation of all enterprise indicators in the industry to which non-listed enterprises belong$LP$ |
| $SDWRDG$ | | The standard deviation of all enterprise indicators in the industry to which non-listed enterprises belong$WRDG$ |
| $QDOP$ | | The quantile difference between the non-listed enterprise index and the industry frontier in the same period$OP$ |
| $QDLP$ | | The quantile difference between the non-listed enterprise index and the industry frontier in the same period$LP$ |
| $QDWRDG$ | | The quantile difference between the non-listed enterprise index and the industry frontier in the same period$WRDG$ |
| $Size$ | Enterprise scale | Natural logarithm of total assets of non-listed companies |
| $Leverage$ | Financial leverage ratio | Ratio of total liabilities to total assets of non-listed companies |
| $Growth$ | Enterprise growth | Year-on-year growth rate of operating income of non-listed companies |
| $CapInt$ | Capital Intensity | Ratio of net fixed assets to number of employees of non-listed companies |
| $IA$ | New Investment | Ratio of new investment amount to total assets of non-listed companies |
| $SA$ | Financing Constraint Index | SA index proposed by Hadlock and Pierce (2010) |

**(2) Model Specification**

To empirically examine Hypothesis I—that an increase (decrease) in the liquidity of listed companies' stocks leads to an increase (decrease) in the TFP of non-listed companies within the same industry, ceteris paribus—we establish the following panel data model with fixed effects:

$$TFP_{i,j,t} = \alpha + \beta ILLIQ_{Mean\,j,t-1}(or\ Liquidity_{j,t-1}) + \sum\nolimits_{k} \gamma_k Control_{k,i,t-1} + Firm\ FE + Year\ FE + \varepsilon_{i,t}, \quad (4)$$

where $TFP_{i,j,t}$ represents the total factor productivity of non-listed company $i$ of industry $j$ on year $t$, $ILLIQ\_Mean_{j,t}$ is the average stock illiquidity of listed companies in the industry $j$ to which the non-listed company $i$ belongs in year $t$, $Liquidity_{j,t}$ is a dummy variable representing the stock liquidity of listed companies in the same industry $j$ in year $t$, $Control_{k,i,t}$ denotes the kth control variable for non-listed company in year $t$, $Firm\ FE$ and $Year\ FE$ denote firm fixed effects and year fixed effects, respectively, and $\varepsilon_{i,t}$ is the error term. $\alpha$ is the constant term, and $\beta$ and $\gamma_k$ are the regression coefficients.

Notably, (I) the incorporation of firm and year fixed effects effectively mitigates potential model misspecification due to omitted variables, and (II) the use of lagged values of explanatory and control variables helps alleviate potential endogeneity issues arising from simultaneity.

The primary focus of this study is on the estimation results of $\beta$ in model (4). If Hypothesis I holds, the estimated value of $\beta$ should be significantly negative when the explanatory variable is $ILLIQ\_Mean_{j,t}$, indicating a significant negative correlation between the stock illiquidity of listed companies and the TFP of non-listed companies within the same industry. Conversely, when the explanatory variable is $Liquidity_{j,t}$, the estimated value of $\beta$ should be significantly positive, indicating that higher stock liquidity of listed companies in the same industry is associated with significantly higher TFP of non-listed companies.

**(3) Sample Data**

This study uses the China Industrial Enterprise Database, covering the period from

1998 to 2013, as the sample for empirical analysis. The industry classification is consistent with that in the China Industrial Enterprise Database. The following data preprocessing steps are conducted based on common practices in existing literature: (1) Listed companies are excluded. (2) Samples with missing major data or information are excluded. (3) Firms that had been established for less than one year are excluded. (4) Firms with total liabilities exceeding total assets are excluded. (5) To avoid the adverse impact of outliers on model estimation, all continuous variables are winsorized at the 1% and 99% levels. After preprocessing, we obtain 1,999,924 firm-year observations, which sufficiently meet the large sample requirement for panel data model estimation.

Descriptive statistics of the main variables are summarized in Table 2. First, the TFP indicators, $OP$, $LP$, and $WRDG$, estimated using the OP, LP, and GMM methods, respectively, exhibit similar distribution characteristics, with means ranging from 5.3 to 5.6 and standard deviations ranging from 1.05 to 1.07. This indicates that the TFP measurement is consistent across different estimation methods. Likewise, the TFP indicators, $OPacf$ and $LPacf$, adjusted using the ACF method exhibit very similar distribution characteristics. Second, the mean value of the average stock illiquidity $ILLIQ\_Mean$ of listed companies within the same industry is 0.227 with a standard deviation of 0.166, indicating substantial variation in stock liquidity levels across different industries, which is consistent with empirical evidence from the Chinese stock market. Lastly, the mean values of the industry innovation imbalance indicators $QDOP$, $QDLP$, and $QDWRDG$ are 1.219, 1.220, and 1.212, respectively, all exceeding the standard deviation of the TFP indicators $OP$, $LP$, and $WRDG$. This suggests that, on average, most sample firms exhibit a significant productivity gap compared to the industry frontier. This indicates that industry innovation imbalance is a prevalent phenomenon in China. Moreover, the maximum values of $QDOP$, $QDLP$, and $QDWRD$ are 4.032, 4.085, and 4.065, respectively, revealing that firms lagging in productivity experience substantial long-term disparities in productivity growth compared to frontier firms.

**Table 2: Descriptive Statistics of Main Variables**

| Variable | N | Mean | S.d. | Min | Median | Max |
|---|---|---|---|---|---|---|
| $OP$ | 1999924 | 5.548 | 1.055 | 2.654 | 5.528 | 8.030 |
| $LP$ | 1999924 | 5.433 | 1.062 | 2.465 | 5.433 | 7.852 |
| $WRDG$ | 1999924 | 5.354 | 1.055 | 2.401 | 5.354 | 7.762 |
| $OPacf$ | 1999924 | 3.535 | 0.987 | 0.714 | 3.540 | 5.892 |
| $LPacf$ | 1999924 | 3.876 | 0.989 | 1.057 | 3.879 | 6.226 |
| $ILLIQ\_Mean$ | 1999924 | 0.227 | 0.166 | 0.029 | 0.177 | 0.665 |
| $Liquidity$ | 1999924 | 0.525 | 0.499 | 0.000 | 1.000 | 1.000 |
| $SDOP$ | 1999924 | 1.029 | 0.099 | 0.841 | 1.034 | 1.277 |
| $SDLP$ | 1999924 | 1.042 | 0.088 | 0.884 | 1.040 | 1.267 |
| $SDWRDG$ | 1999924 | 1.035 | 0.088 | 0.876 | 1.035 | 1.256 |
| $QDOP$ | 1999924 | 1.219 | 1.001 | -1.079 | 1.208 | 4.032 |
| $QDLP$ | 1999924 | 1.220 | 1.006 | -1.054 | 1.199 | 4.085 |
| $QDWRDG$ | 1999924 | 1.212 | 1.000 | -1.048 | 1.190 | 4.065 |
| $Size$ | 1999924 | 10.021 | 1.397 | 7.153 | 9.880 | 13.990 |
| $Leverage$ | 1999924 | 0.529 | 0.257 | 0.012 | 0.548 | 0.978 |
| $Growth$ | 1999924 | 0.327 | 0.875 | -0.755 | 0.139 | 5.670 |
| $CapInt$ | 1999924 | 3.781 | 1.291 | 0.297 | 3.816 | 6.911 |
| $IA$ | 1999924 | 0.045 | 0.224 | -1.094 | 0.024 | 0.728 |
| $SA$ | 1999924 | -3.430 | 0.415 | -4.989 | -3.372 | -2.346 |

# 4. Empirical Results

### (1) Core Empirical Results

Table 3 presents the estimation results of model (4), which examines the impact of stock liquidity of listed companies on the TFP of non-listed firms in the same industry. In Panel A, the explanatory variable is $ILLIQ\_Mean$, while in Panel B, it is $Liquidity$. The results indicate that in Panel A, the estimated regression coefficients of $ILLIQ\_Mean$ are significantly negative at the 1% level. These results remain consistent even when control variables are included. This indicates that the level of stock illiquidity of listed companies is significantly negatively correlated with the TFP of non-listed firms in the same industry, thus confirming Hypothesis I. In Panel B, the estimated regression coefficients of Liquidity are significantly positive at the 1% level and remain robust after including control variables. This suggests that non-listed firms in industries with higher stock liquidity among listed companies exhibit significantly higher TFP, further confirming Hypothesis I. Therefore, the core empirical results demonstrate that, all else being equal, an increase in the stock liquidity of listed companies leads to an increase in the TFP of non-listed firms in the same industry. Conversely, a decrease in stock liquidity leads to a decrease in TFP.

**Table 3: Impact of Stock Liquidity of Listed Companies on the TFP of Non-Listed Firms in the Same Industry**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $OP$ | | $LP$ | | $WRDG$ | |
| | Panel A: The independent variable is $ILLIQ\_Mean$ | | | | | |
| $ILLIQ\_Mean$ | -0.155*** | -0.145*** | -0.155*** | -0.146*** | -0.154*** | -0.146*** |
| | (-12.88) | (-12.29) | (-12.71) | (-12.31) | (-12.69) | (-12.29) |
| $Size$ | | 0.156*** | | 0.160*** | | 0.155*** |
| | | (66.95) | | (68.70) | | (66.75) |
| $Leverage$ | | -0.075*** | | -0.084*** | | -0.082*** |
| | | (-14.28) | | (-15.94) | | (-15.64) |
| $Growth$ | | 0.067*** | | 0.067*** | | 0.067*** |
| | | (73.73) | | (73.22) | | (73.29) |
| $CapInt$ | | -0.005*** | | -0.057*** | | -0.053*** |
| | | (-3.35) | | (-37.51) | | (-35.03) |
| $IA$ | | -0.071*** | | -0.039*** | | -0.041*** |
| | | (-18.84) | | (-10.35) | | (-10.99) |
| $SA$ | | 0.079*** | | 0.056*** | | 0.058*** |
| | | (16.02) | | (11.39) | | (11.78) |
| Constant | 5.346*** | 4.169*** | 5.247*** | 4.133*** | 5.168*** | 4.092*** |
| | (907.35) | (137.23) | (879.11) | (135.89) | (868.69) | (134.79) |
| R2 | 0.067 | 0.085 | 0.073 | 0.090 | 0.071 | 0.087 |
| | Panel B: The independent variable is Liquidity | | | | | |
| $Liquidity$ | 0.023*** | 0.022*** | 0.022*** | 0.021*** | 0.022*** | 0.021*** |
| | (14.48) | (14.20) | (13.49) | (13.52) | (13.56) | (13.57) |
| $Size$ | | 0.156*** | | 0.160*** | | 0.155*** |
| | | (67.01) | | (68.75) | | (66.80) |
| $Leverage$ | | -0.075*** | | -0.084*** | | -0.082*** |
| | | (-14.25) | | (-15.91) | | (-15.62) |
| $Growth$ | | 0.067*** | | 0.067*** | | 0.067*** |
| | | (73.75) | | (73.25) | | (73.31) |
| $CapInt$ | | -0.005*** | | -0.057*** | | -0.053*** |
| | | (-3.38) | | (-37.54) | | (-35.06) |
| $IA$ | | -0.071*** | | -0.039*** | | -0.041*** |
| | | (-18.87) | | (-10.38) | | (-11.01) |
| $SA$ | | 0.079*** | | 0.056*** | | 0.058*** |
| | | (15.95) | | (11.33) | | (11.72) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Constant | 5.272*** | 4.097*** | 5.175*** | 4.061*** | 5.095*** | 4.020*** |
| | (1426.97) | (136.74) | (1380.21) | (135.39) | (1364.67) | (134.28) |
| R2 | 0.067 | 0.085 | 0.073 | 0.090 | 0.071 | 0.087 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Robust | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1374103 | 1374103 | 1374103 | 1374103 | 1374103 | 1374103 |

Note: Table 3 reports the estimation results of model (4), examining the impact of stock liquidity on the TFP of non-listed firms in the same industry. Panel A uses $ILLIQ\_Mean$ as the explanatory variable, and Panel B uses Liquidity. $OP$, $LP$, and $WRDG$ indicate TFP estimates of non-listed firms using the OP method, LP method, and GMM method, respectively. $ILLIQ\_Mean$ is the average stock illiquidity of listed companies in the industry of non-listed firms. $Liquidity$ is a dummy variable (equal to 1 if $ILLIQ\_Mean$ is in the bottom 50% of the sample for the same period, otherwise 0). $Size$ denotes firm size, $Leverage$ denotes financial leverage, $Growth$ denotes firm growth, $CapInt$ denotes capital intensity, $IA$ denotes new investment, and $SA$ denotes the financing constraint index. All explanatory and control variables are lagged by one period. Values in parentheses are t-statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

## (2) Robustness Checks

To ensure the robustness of the core empirical results, we perform a series of robustness checks.

### 1. Replacing Explanatory Variables

Considering that the average stock illiquidity of listed companies in the industry ($ILLIQ\_Mean$) may be affected by extreme outliers, we replace the explanatory variable in model (4) with the 25th percentile, median, and 75th percentile values of stock illiquidity ($ILLIQ\_Q25$、$ILLIQ\_Median$ and $ILLIQ\_Q75$), respectively, and re-estimate the model as a robustness check. Table 4 reports the estimation results after substituting the explanatory variables. The results show that the estimated regression coefficients of $ILLIQ\_Q25$、$ILLIQ\_Median$ and $ILLIQ\_Q75$ are significantly negative at the 1% level, consistent with the core empirical results. This indicates that the core empirical results are robust to extreme outliers in stock illiquidity.

**Table 4: Estimation Results of Model (4) after Replacing Explanatory Variables**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | | $OP$ | | | $LP$ | | | $WRDG$ | |
| $ILLIQ\_Q25$ | -0.185*** | | | -0.188*** | | | -0.187*** | | |
| | (-14.52) | | | (-14.67) | | | (-14.64) | | |
| $ILLIQ\_Median$ | | -0.119*** | | | -0.121*** | | | -0.121*** | |
| | | (-12.59) | | | (-12.65) | | | (-12.63) | |
| $ILLIQ\_Q75$ | | | -0.072*** | | | -0.074*** | | | -0.074*** |
| | | | (-9.09) | | | (-9.16) | | | (-9.16) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Robust | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1374103 | 1374103 | 1374103 | 1374103 | 1374103 | 1374103 | 1374103 | 1374103 | 1374103 |
| R2 | 0.085 | 0.085 | 0.085 | 0.090 | 0.090 | 0.090 | 0.087 | 0.087 | 0.087 |

Note: Table 4 reports the estimation results after replacing the explanatory variable with the percentiles of stock illiquidity in the industry of non-listed firms. $ILLIQ\_Q25$ is the 25th percentile, $ILLIQ\_Median$ is the 50th percentile (median), and $ILLIQ\_Q75$ is the 75th percentile of the ILLIQ indicator. Values in parentheses are t-statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. To save space and enhance readability, control variables and intercepts are not reported.

## 2. Replacing Dependent Variables

Ackerberg et al. (2015) point out that the assumptions of the OP and LP methods might overlook the costs associated with adjusting factor inputs in response to productivity shocks, potentially leading to severe multicollinearity issues in the first-step estimation results. To address this, we use the ACF adjustment method proposed by Ackerberg et al. (2015) to adjust the $OP$ and $LP$ indicators, obtaining $OPacf$ and $LPacf$. We then replace the dependent variables in model (4) with these adjusted indicators for robustness checks. Table 5 reports the estimation results of model (4) after substituting the dependent variables with the adjusted TFP indicators. The results show that the estimated regression coefficients of $ILLIQ\_Mean$ are significantly negative at the 1% level, while the estimated regression coefficients of $Liquidity$ are significantly positive at the 1% level, consistent with the core empirical results. This indicates that the core empirical results are robust to different TFP estimation methods.

**Table 5: Estimation Results of Model (4) after Replacing Dependent Variables**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $OPacf$ | | $LPacf$ | |
| $ILLIQ\_Mean$ | -0.137*** | | -0.139*** | |
| | (-11.57) | | (-11.72) | |
| $Liquidity$ | | 0.021*** | | 0.021*** |
| | | (13.42) | | (13.59) |
| Control Variables | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Robust | Yes | Yes | Yes | Yes |
| N | 1374103 | 1374103 | 1374103 | 1374103 |
| R2 | 0.050 | 0.050 | 0.054 | 0.054 |

Note: Table 5 reports the estimation results after replacing the dependent variables with the ACF-adjusted TFP indicators. OPacf and LPacf are the TFP indicators adjusted using the ACF method for the OP and LP methodologies, respectively. Values in parentheses are t-statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. To save space and enhance readability, control variables and intercepts are not reported.

### 3. Grouping by Ownership Type of Non-Listed Firms

Considering that the operational objectives and governance structures of non-listed firms may vary significantly with ownership type (Bai et al., 2006; Lin et al., 1998), potentially affecting the transmission mechanism of stock liquidity, we divide the sample into "state-owned enterprises" and "non-state-owned enterprises" groups and conduct grouped regressions based on model (4). Table 6 reports the estimation results of model (4) after stratifying the sample by the ownership type of non-listed firms. The results show that in both groups, the estimated regression coefficients of Liquidity are significantly positive at the 1% level, consistent with the core empirical results. This indicates that the core empirical results are robust to the ownership type of non-listed firms.

**Table 6: Estimation Results of Model (4) after Grouping by Ownership Type of Non-Listed Firms**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $OP$ | $LP$ | $WRDG$ | $OP$ | $LP$ | $WRDG$ |
| | State-owned enterprises | | | Non-state-owned enterprises | | |
| $Liquidity$ | 0.020*** | 0.020*** | 0.020*** | 0.022*** | 0.020*** | 0.020*** |
| | (3.56) | (3.54) | (3.56) | (13.27) | (12.55) | (12.58) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Robust | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 100248 | 100248 | 100248 | 1273855 | 1273855 | 1273855 |
| R2 | 0.042 | 0.041 | 0.041 | 0.087 | 0.092 | 0.090 |

Note: Table 6 reports the estimation results after grouping by the ownership type of non-listed firms. Columns (1) to (3) present the regression samples of state-owned non-listed firms, and columns (4) to (6) present the regression samples of non-state-owned non-listed firms. Values in parentheses are t-statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. To save space and enhance readability, control variables and intercepts are not reported.

## 4. Grouping by Geographic Region of Non-Listed Firms

Considering that vast geographical expanse of China results in uneven regional development, with significant differences in market environment, business climate, and legal environment between more developed eastern regions (Beijing, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong) and less developed central and western regions (all other regions), we divide the sample into "eastern regions" and "central and western regions" groups and conduct grouped regressions based on model (4). Table 7 reports the estimation results of model (4) after stratifying the sample by the geographic region of non-listed firms. The results show that in both groups, the estimated regression coefficients of Liquidity are significantly positive at the 1% level, consistent with the core empirical results. This indicates that the core empirical results are robust to the geographic region of non-listed firms.

**Table 7: Estimation Results of Model (4) after Grouping by Geographic Region of Non-Listed Firms**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $OP$ | $LP$ | $WRDG$ | $OP$ | $LP$ | $WRDG$ |
| | Eastern region | | | Central and western regions | | |
| $Liquidity$ | 0.016*** | 0.015*** | 0.016*** | 0.019*** | 0.019*** | 0.019*** |
| | (8.82) | (8.35) | (8.38) | (6.60) | (6.58) | (6.60) |
| $Control\ Variables$ | Yes | Yes | Yes | Yes | Yes | Yes |
| $Firm\ FE$ | Yes | Yes | Yes | Yes | Yes | Yes |
| $Year\ FE$ | Yes | Yes | Yes | Yes | Yes | Yes |
| $Robust$ | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 912989 | 912989 | 912989 | 461114 | 461114 | 461114 |
| $R2$ | 0.083 | 0.085 | 0.083 | 0.109 | 0.113 | 0.111 |

Note: Table 7 reports the estimation results of model (4) after grouping by the region of non-listed firms. Columns (1) to (3) use non-listed firms in the more developed eastern regions of China (Beijing, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, and Guangdong) as the regression sample, while columns (4) to (6) use non-listed firms in the less developed central and western regions of China (excluding the aforementioned eastern regions) as the regression sample. The values in parentheses are t-statistics. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. For brevity and ease of reading, the estimation results for control variables and intercept terms are not reported in the table.

## 5. Grouped Regressions Based on the Timing of the 2008 Financial Crisis

Considering the significant impact of the 2008 global financial crisis on the environment and institutions of the Chinese financial market, which may affect the transmission mechanism by which stock liquidity of listed companies influences the TFP of non-listed firms in the same industry, we divide the sample into "before the 2008 financial crisis" (i.e., 1998-2007) and "after the 2008 financial crisis" (i.e., 2008-2013) groups and conduct grouped regressions based on model (4). Table 8 reports the estimation results of model (4) after stratifying the sample by the timing of the 2008 financial crisis. The results show that, in both groups, the regression coefficients of the explanatory variable $Liquidity$ are almost all significantly positive at the 1% level (only in the first group regression, the regression coefficient of the explanatory variable $Liquidity$ is significantly positive at the 5% level). These results are consistent with the main empirical findings of this study. This indicates that the core empirical results of this study are robust to the choice of the sample period.

**Table 8: Estimation Results of Model (4) Grouped by the Timing of the 2008 Financial Crisis**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|

| | $OP$ | $LP$ | $WRDG$ | $OP$ | $LP$ | $WRDG$ |
|---|---|---|---|---|---|---|
| | Before the 2008 financial crisis | | | After the 2008 financial crisis | | |
| $Liquidity$ | 0.004** | 0.005*** | 0.005*** | 0.023*** | 0.012*** | 0.013*** |
| | (2.47) | (2.95) | (2.91) | (6.85) | (3.71) | (4.03) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Robust | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 827322 | 827322 | 827322 | 546781 | 546781 | 546781 |
| R2 | 0.075 | 0.067 | 0.067 | 0.105 | 0.126 | 0.121 |

Note: Table 8 reports the estimation results of model (4) grouped by the timing of the 2008 financial crisis. Columns (1) to (3) use sample data from before the 2008 financial crisis (i.e., 1998-2007), and columns (4) to (6) use sample data from after the 2008 financial crisis (i.e., 2008-2013). The values in parentheses are t-statistics. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. For brevity and ease of reading, the estimation results for control variables and intercept terms are not reported in the table.

In summary, a series of robustness checks demonstrates that the core empirical findings of this study are robust to various specifications and sample partitions.

# 5.Mechanism Analysis

**(1) Methodology for Mechanism Testing**

To further examine whether the transmission mechanism aligns with Hypothesis II, we construct the following moderated effect model for mechanism analysis:

$$TFP_{i,j,t} = \alpha + \beta_1 Liquidity_{j,t-1} + \beta_2 NCI_{i,j,t-1} + \beta_3 Liquidity_{j,t-1} \times NCI_{i,j,t-1} + \sum_k \gamma_k Control_{k,i,t-1} + Firm\ FE + Year\ FE + \varepsilon_{i,t} \quad (5)$$

where $NCI_{i,j,t}$ represents the extent of innovation imbalance in the industry $j$ for non-listed firm $i$ in year $t$. This study measures the extent of innovation imbalance in an industry using two approaches. First, we use the standard deviation of TFP among all firms within the industry ($SDOP$, $SDLP$, and $SDWRDG$). Second, we use the difference between the 90th and 10th percentiles of TFP within the industry ($QDOP$, $QDLP$, and $QDWRDG$). The key focus is on the estimation results of $\beta_2$ and $\beta_3$ in model (5). The partial derivative of $TFP_{i,j,t}$ with respect to $NCI_{i,j,t-1}$ is $\beta_2 + \beta_3 Liquidity_{j,t-1}$. Since $Liquidity_{j,t-1}$ is a binary variable, the partial derivative equals $\beta_2 + \beta_3$ when ($Liquidity_{j,t-1}$= 1) (indicating high stock liquidity of listed companies in the same industry), and equals $\beta_2$ when $Liquidity_{j,t-1}$ = 0) (indicating low stock liquidity of listed companies in the same industry). Therefore, the regression coefficient $\beta_2$ reflects the marginal impact of innovation imbalance on firm TFP independent of industry stock liquidity differences. The regression coefficient $\beta_3$ reflects the differential marginal impact of innovation imbalance on firm TFP between non-listed firms in industries with high versus low stock liquidity. According to Hypothesis II, we expect the estimated value of $\beta_2$ to be significantly negative, indicating that innovation imbalance significantly inhibits TFP growth of non-listed firms. We also expect the estimated value of $\beta_3$ to be significantly positive, indicating that higher stock liquidity of listed companies in the same industry promotes TFP growth of non-listed firms by inhibiting the negative effects of innovation imbalance.

**(2) Results of Mechanism Analysis**

Table 9 reports the estimation results of model (5), which examines the mechanism by which stock liquidity of listed companies influences the TFP of non-listed companies in the same industry. The results show that the regression coefficients of innovation imbalance variables ($SDOP$、$SDLP$、$SDWRDG$、$QDOP$、$QDLP$ and $QDWRDG$) are all significantly negative at the 1% level, indicating that innovation imbalance significantly inhibits TFP growth of non-listed firms. At the same time, the regression coefficients of the interaction terms ($Liquidity \times SDOP$、$Liquidity \times SDLP$、$Liquidity \times SDWRDG$、$Liquidity \times QDOP$、$Liquidity \times QDLP$ and $Liquidity \times QDWRDG$) are all significantly positive at the 1% level, indicating that higher stock liquidity of listed companies in the same industry promotes TFP growth of non-listed firms by inhibiting the negative effects of innovation imbalance. These empirical results strongly support Hypothesis II, which states that an increase in stock liquidity of listed companies promotes TFP growth of non-listed firms in the same industry by inhibiting the negative effects of innovation imbalance. Conversely, a decrease in stock liquidity inhibits TFP growth by exacerbating these negative effects.

**Table 9: Mechanism Testing of the Influence of Stock Liquidity of Listed Companies on the TFP of Non-Listed Companies in the Same Industry**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $OP$ | $LP$ | $WRDG$ | $OP$ | $LP$ | $WRDG$ |
| $Liquidity$ | -0.215*** | -0.255*** | -0.258*** | 0.010*** | 0.008*** | 0.008*** |
| | (-12.40) | (-13.19) | (-13.42) | (4.20) | (3.69) | (3.66) |
| $SDOP$ | -0.145*** | | | | | |
| | (-5.10) | | | | | |
| $Liquidity \times SDOP$ | 0.235*** | | | | | |
| | (13.55) | | | | | |
| $SDLP$ | | -0.202*** | | | | |
| | | (-6.95) | | | | |
| $Liquidity \times SDLP$ | | 0.270*** | | | | |
| | | (14.18) | | | | |
| $SDWRDG$ | | | -0.199*** | | | |
| | | | (-6.84) | | | |
| $Liquidity \times SDWRDG$ | | | 0.275*** | | | |
| | | | (14.41) | | | |
| $QDOP$ | | | | -0.148*** | | |
| | | | | (-83.01) | | |
| $Liquidity \times QDOP$ | | | | 0.013*** | | |
| | | | | (7.52) | | |
| $QDLP$ | | | | | -0.151*** | |
| | | | | | (-84.89) | |
| $Liquidity \times QDLP$ | | | | | 0.013*** | |
| | | | | | (7.55) | |
| $QDWRDG$ | | | | | | -0.151*** |
| | | | | | | (-84.44) |
| $Liquidity \times QDWRDG$ | | | | | | 0.013*** |
| | | | | | | (7.59) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Robust | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1374103 | 1374103 | 1374103 | 1374103 | 1374103 | 1374103 |
| R2 | 0.085 | 0.090 | 0.088 | 0.100 | 0.106 | 0.104 |

Note: Table 9 reports the estimation results of model (5). Columns (1) to (3) use the standard deviation of TFP within the industry to measure the extent of innovation imbalance, while columns (4) to (6) use the difference in TFP percentiles within the industry to measure the extent of innovation imbalance. $SDOP$, $SDLP$, and $SDWRDG$ represent the standard deviation of $OP$, $LP$, and $WRDG$, respectively, while $QDOP$, $QDLP$, and $QDWRDG$ represent the difference between the 90th and 10th percentiles of $OP$, $LP$, and $WRDG$, respectively. The values in parentheses are t-statistics. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. For brevity and ease of reading, the estimation results for control variables and intercept terms are not reported in the table.

Hypothesis II also suggests a corollary: when the stock liquidity of listed companies within the same industry increases, the TFP growth of non-listed firms should mainly come from firms with relatively lower productivity. Andrews et al. (2016) are the first to propose a similar viewpoint. However, there is still a lack of empirical evidence from the perspective of stock liquidity. This study conducts empirical research by dividing the sample into "low-productivity firms" and "high-productivity firms" within each industry for each year based on TFP levels. We then perform grouped regressions using model (5). If the corollary holds, the expected results of model (5) should be more pronounced in the "low-productivity firms" group. Table 10 reports the results of the grouped regressions. The results show that only in the "low-productivity firms" group are the regression coefficients of the innovation imbalance variables ($SDOP$、$SDLP$、$SDWRDG$) significantly negative at the 1% level. In the "high-productivity firms" group, the regression coefficients of the innovation imbalance variables ($SDOP$、$SDLP$、$SDWRDG$) are significantly positive at the 1% level. These empirical results indicate that the inhibitory effect of innovation imbalance on TFP growth primarily stems from non-listed firms with lower productivity. Additionally, when the stock liquidity of listed companies within the same industry increases, the TFP growth of non-listed firms mainly comes from those firms with relatively lower productivity. These findings strongly support the corollary that TFP growth is primarily driven by low-productivity firms when stock liquidity increases.

**Table 10: TFP Growth Mainly Driven by Low-Productivity Firms**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $OP$ | $LP$ | $WRDG$ | $OP$ | $LP$ | $WRDG$ |
| | Productivity backward enterprises | | | Productivity leading enterprises | | |
| $Liquidity$ | -0.246*** | -0.317*** | -0.327*** | -0.182*** | -0.233*** | -0.234*** |
| | (-11.25) | (-12.74) | (-13.27) | (-11.21) | (-13.10) | (-13.26) |
| $SDOP$ | -0.213*** | | | 0.174*** | | |
| | (-6.10) | | | (6.58) | | |
| $Liquidity \times SDOP$ | 0.267*** | | | 0.199*** | | |
| | (12.15) | | | (12.28) | | |
| $SDLP$ | | -0.299*** | | | 0.085*** | |
| | | (-8.33) | | | (3.25) | |
| $Liquidity \times SDLP$ | | 0.330*** | | | 0.245*** | |
| | | (13.48) | | | (14.07) | |
| $SDWRDG$ | | | -0.299*** | | | 0.090*** |
| | | | (-8.33) | | | (3.43) |
| $Liquidity \times SDWRDG$ | | | 0.343*** | | | 0.248*** |
| | | | (14.01) | | | (14.23) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Robust | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 660353 | 658005 | 658728 | 713750 | 716098 | 715375 |
| R2 | 0.119 | 0.106 | 0.104 | 0.218 | 0.243 | 0.239 |

Note: Table 10 reports the estimation results of model (5) grouped by firms' productivity levels. Columns (1) to (3) use non-listed firms with productivity below the industry median as the sample, while columns (4) to (6) use non-listed firms with productivity above the industry median as the sample. The values in parentheses are t-statistics. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. For brevity and ease of reading, the estimation results for control variables and intercept terms are not reported in the table.

### (3) Mechanism Analysis

We propose three potential mechanisms through which stock liquidity of listed companies affects the negative effects of innovation imbalance within an industry: the information mechanism, the financing mechanism, and the governance mechanism (i.e., Hypotheses IIA, IIB, and IIC). To identify which mechanism is significantly effective, we conduct empirical research by iteratively grouping the sample based on information efficiency, financing constraints, and agency costs. We then perform grouped regressions using model (5). If the information mechanism holds, the expected results of model (5) should be more pronounced in the group with lower information efficiency. If the financing mechanism holds, the expected results of model (5) should be more pronounced in the group with tighter financing constraints.

If the governance mechanism holds, the expected results of model (5) should be more pronounced in the group with higher agency costs.

**1. Information mechanism**

We use the mean price synchronicity indicator ($SYN$) of listed companies in the same industry (Jin and Myers, 2006; Roll, 1988) as a measure of information efficiency. When the mean $SYN$ of listed companies in the same industry is above the sample median for the same period, the industry is categorized as the "high information efficiency" group; otherwise, it is categorized as the "low information efficiency" group. Table 11 reports the results of the information mechanism analysis. The results show that the regression coefficients of innovation imbalance variables ($SDOP$、$SDLP$、$SDWRDG$ are not significantly different from zero at the 10% level in the "high information efficiency" group. In contrast, they are significantly negative at the 1% level in the "low information efficiency" group. This indicates that the expected results of model (5) are more pronounced in the group with lower information efficiency. These results align with expectations, demonstrating that the information mechanism through which stock liquidity of listed companies affects the negative effects of industry innovation imbalance is valid.

**Table 11: Results of Information Mechanism**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $OP$ | $LP$ | $WRDG$ | $OP$ | $LP$ | $WRDG$ |
| | High information efficiency | | | Low information efficiency | | |
| $Liquidity$ | -0.211*** | -0.271*** | -0.273*** | -0.133*** | -0.122*** | -0.131*** |
| | (-8.07) | (-9.35) | (-9.46) | (-4.59) | (-3.65) | (-3.95) |
| $SDOP$ | 0.048 | | | -0.274*** | | |
| | (1.17) | | | (-6.39) | | |
| $Liquidity \times SDOP$ | 0.227*** | | | 0.169*** | | |
| | (8.77) | | | (5.76) | | |
| $SDLP$ | | -0.053 | | | -0.275*** | |
| | | (-1.24) | | | (-6.36) | |
| $Liquidity \times SDLP$ | | 0.283*** | | | 0.150*** | |
| | | (10.01) | | | (4.53) | |
| $SDWRDG$ | | | -0.046 | | | -0.278*** |
| | | | (-1.07) | | | (-6.41) |
| $Liquidity \times SDWRDG$ | | | 0.286*** | | | 0.160*** |
| | | | (10.12) | | | (4.84) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Robust | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 731454 | 731454 | 731454 | 637548 | 637548 | 637548 |
| R2 | 0.088 | 0.095 | 0.092 | 0.087 | 0.090 | 0.087 |

Note: Table 11 reports the estimation results of model (5) grouped by information efficiency. Columns (1) to (3) use non-listed firms in industries where the mean SYN of listed companies is below the sample median for the same period as the sample, while columns (4) to (6) use non-listed firms in industries where the mean SYN of listed companies is above the sample median for the same period as the sample. The values in parentheses are t-statistics. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. For brevity and ease of reading, the estimation results for control variables and intercept terms are not reported in the table.

## 2. Financing mechanism

We measure the financing constraints of non-listed firms using the SA index. When the SA index of non-listed firms is above the sample median within the same industry for the same period, the firm is categorized as the "tight financing constraints" group; otherwise, it is categorized as the "loose financing constraints" group. Table 12 reports the results of the financing mechanism analysis. The results show that the regression coefficients of innovation imbalance variables ($SDOP$、$SDLP$、$SDWRDG$) are significantly negative at the 1% level in the "tight financing constraints" group; meanwhile, in the "loose financing constraints" group, the regression coefficients of innovation imbalance variables ($SDOP$、$SDLP$、$SDWRDG$) are significantly negative at the 10%, 1%, and 1% levels, respectively. This indicates that the expected results of model (5) do not significantly differ between groups with different levels of financing constraints. These results are contrary to expectations, suggesting that the financing mechanism through which stock liquidity of listed companies affects the negative effects of innovation imbalance in the industry is not valid.

**Table 12: Results of Financing Mechanism**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $OP$ | $LP$ | $WRDG$ | $OP$ | $LP$ | $WRDG$ |
| | Tight financing constraints | | | Loose financing constraints | | |
| $Liquidity$ | -0.201*** | -0.231*** | -0.234*** | -0.197*** | -0.264*** | -0.265*** |
| | (-8.61) | (-8.82) | (-9.01) | (-7.22) | (-8.72) | (-8.81) |
| $SDOP$ | -0.188*** | | | -0.080* | | |
| | (-4.74) | | | (-1.82) | | |
| $Liquidity \times SDOP$ | 0.219*** | | | 0.218*** | | |
| | (9.31) | | | (8.05) | | |
| $SDLP$ | | -0.242*** | | | -0.146*** | |
| | | (-5.98) | | | (-3.27) | |
| $Liquidity \times SDLP$ | | 0.243*** | | | 0.279*** | |
| | | (9.42) | | | (9.44) | |
| $SDWRDG$ | | | -0.240*** | | | -0.143*** |
| | | | (-5.91) | | | (-3.18) |
| $Liquidity \times SDWRDG$ | | | 0.248*** | | | 0.283*** |
| | | | (9.61) | | | (9.53) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Robust | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 744818 | 744818 | 744818 | 629285 | 629285 | 629285 |
| R2 | 0.076 | 0.083 | 0.081 | 0.093 | 0.092 | 0.090 |

Note: Table 12 reports the estimation results of model (5) grouped by financing constraints. Columns (1) to (3) use non-listed firms with $SA$ indexes below the sample median within the same industry for the same period as the sample, while columns (4) to (6) use non-listed firms with $SA$ indexes above the sample median within the same industry for the same period as the sample. The values in parentheses are t-statistics. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. For brevity and ease of reading, the estimation results for control variables and intercept terms are not reported in the table.

### 3. Governance mechanism

In this study, we measure the agency costs of non-listed firms using the ratio of management expenses to operating revenue. When the ratio of management expenses to operating revenue is below the median of the same industry sample for the same period, the firms are categorized as the "low agency cost" group. Conversely, when the ratio is above the median, they are categorized as the "high agency cost" group. Table 13 reports the results of the governance mechanism analysis. The results show that in the "low agency cost" group, the estimated regression coefficients of the innovation imbalance variables $SDOP$、$SDLP$、$SDWRDG$ are not significantly different from zero at the 10% level. However, in the "high agency cost" group, the estimated regression coefficients of the innovation imbalance variables $SDOP$、$SDLP$、$SDWRDG$ are significantly negative at the 1% level. This indicates that the expected results of model (5) are more pronounced in the group with higher agency costs. These findings are consistent with our expectations, confirming that the governance mechanism through which stock liquidity of listed companies influences the negative effects of industry innovation imbalance is valid.

In summary, a series of mechanism analysis results indicate that the information mechanism and the governance mechanism through which stock liquidity of listed companies impacts the negative effects of industry innovation imbalance are significant. However, the financing mechanism is not significant.

**Table 13: Results of Governance Mechanism**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $OP$ | $LP$ | $WRDG$ | $OP$ | $LP$ | $WRDG$ |
| | Low agency costs | | | High agency costs | | |
| $Liquidity$ | -0.084*** | -0.115*** | -0.117*** | -0.265*** | -0.304*** | -0.306*** |
| | (-3.26) | (-4.00) | (-4.12) | (-10.92) | (-11.15) | (-11.30) |
| $SDOP$ | 0.042 | | | -0.288*** | | |
| | (1.04) | | | (-7.12) | | |
| $Liquidity \times SDOP$ | 0.101*** | | | 0.288*** | | |
| | (3.92) | | | (11.90) | | |
| $SDLP$ | | 0.009 | | | -0.361*** | |
| | | (0.22) | | | (-8.72) | |
| $Liquidity \times SDLP$ | | 0.128*** | | | 0.320*** | |
| | | (4.52) | | | (12.01) | |
| $SDWRDG$ | | | 0.019 | | | -0.363*** |
| | | | (0.45) | | | (-8.76) |
| $Liquidity \times SDWRDG$ | | | 0.132*** | | | 0.325*** |
| | | | (4.64) | | | (12.17) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Robust | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 672443 | 672443 | 672443 | 701633 | 701633 | 701633 |
| R2 | 0.135 | 0.119 | 0.118 | 0.057 | 0.072 | 0.069 |

Note: Table 13 reports the estimation results of model (5) after grouping according to the level of governance costs. Among them, columns (1) to (3) use unlisted companies whose ratio of administrative expenses to operating income is lower than the median of the same industry sample in the same period as samples, and columns (4) to (6) use the ratio of administrative expenses to operating income. Unlisted companies that are higher than the median of samples in the same industry during the same period are used as samples. T-statistics are shown in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. To save space and facilitate reading, the table does not report the estimated results of control variables and intercept terms.

# 6.Conclusion

Can the stock market indirectly promote the TFP growth of non-listed firms through non-financing mechanisms? This paper addresses this question from the perspective of stock liquidity.

First, this paper theoretically elucidates how increased stock liquidity of listed companies can mitigate the negative impacts of innovation imbalance on TFP, thereby promoting the TFP growth of non-listed firms. The extent to which a firm's productivity benefits from a major breakthrough in an emerging general-purpose technology depends on how much complementary synergistic innovation occurs within its industry based on the emerging general-purpose technology (Acemoglu et al., 2024). Complementary innovation activities are widely dispersed across the economy. These activities are characterized by uncertainty and information asymmetry. Therefore, incentivizing and coordinating these activities is highly challenging (Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1996). Increased stock liquidity of listed companies can mitigate the adverse effects of innovation imbalance on TFP growth within the same industry. This is achieved through three mechanisms: (1) facilitating private information learning (information mechanism), (2) alleviating financing constraints (financing mechanism), and (3) improving corporate governance (governance mechanism) among non-listed firms. Based on this theoretical foundation, several hypotheses are proposed.

Subsequently, this paper designs a series of empirical analyses. These analyses are used to test the proposed hypotheses. First, a fixed-effects panel data model is constructed to examine the impact of stock liquidity of listed companies on the TFP of non-listed firms within the same industry. Results show that, all else being equal, increases (decreases) in the stock liquidity of listed companies lead to increases (decreases) in the TFP of non-listed firms within the same industry. This demonstrates a significant spillover effect of stock liquidity. The finding is robust to various tests including the replacement of explanatory variables, dependent variables, group regression based on the ownership structure of non-listed firms, regional group regression, and pre- and post-2008 financial crisis group regression. Second, a moderated fixed-effects panel model is employed to explore the mechanisms through which stock liquidity affects TFP growth. Mechanism tests indicate that increased stock liquidity mitigated the negative impacts of innovation imbalance, primarily benefiting the TFP growth of productivity-lagging firms, consistent with findings by Andrews et al. (2016). Further analysis shows that the information mechanism and governance mechanism through which stock liquidity impacts innovation imbalance are significant, while the financing mechanism is not.

This study demonstrates that stock liquidity of listed companies has a significant spillover effect on the TFP of non-listed firms within the same industry, expanding the theoretical and practical implications of stock market development for economic growth. The research establishes a theoretical link between stock liquidity of listed companies and the TFP of non-listed firms from the perspective of industry innovation imbalance. Additionally, strong empirical evidence supports the core arguments of this paper. This evidence clarifies the mechanisms through which stock liquidity impacts the TFP of non-listed firms within the same industry.

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