Technology-Finance City Pilot Program and Capital Market Mispricing

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Abstract. In modern capital markets, the development of technology finance enhances corporate financing efficiency while also exerting a profound impact on capital market pricing mechanisms. Using data from Chinese listed companies from 2008 to 2022, this paper examines the effect of the Technology-Finance City Pilot Program on corporate asset mispricing. The findings indicate that the pilot program significantly alleviates asset mispricing, and this conclusion remains robust after a series of robustness tests. Further heterogeneity analysis reveals that this mitigating effect is more pronounced in eastern regions, non-state-owned enterprises, and non-environmentally focused cities. Mechanism analysis suggests that the pilot program effectively reduces asset mispricing through improving information transparency, enhancing market liquidity, and optimizing investor behavior. This study provides empirical evidence for the formulation and optimization of technology finance policies, contributing to improving capital market pricing efficiency and promoting the rational allocation of financial resources.

Keywords: Technology-Finance Pilot Program; Asset Mispricing; Information Transparency; Market Liquidity; Investor Behavior.

1. Introduction

China's economy has experienced decades of rapid growth, during which its financial market has also expanded significantly, becoming a vital engine driving economic development. The healthy and stable growth of the economy and financial markets hinges on financial market stability, as the sound operation of the financial system serves as a cornerstone for sustained economic growth. As General Secretary Xi Jinping emphasized during the opening ceremony of a seminar for provincial and ministerial-level officials on promoting high-quality financial development, "Developing fintech is an important measure to empower technological innovation with financial resources, promote high-quality financial development, and accelerate the construction of a financial powerhouse." This statement highlights the significant role of fintech development in promoting a healthy capital market.

Although the market size of China's fintech industry reached a historical high of RMB 1.7427 trillion in 2023, the synergy between technological innovation and the fintech ecosystem has not yet reached an optimal state. Several challenges persist: the difficulty in valuing innovation-driven entities, the mismatch between traditional banking services and innovation needs, insufficient participation and support from relevant stakeholders, and inadequate supporting mechanisms for fintech. These issues not only constrain the vitality of technological innovation but also hinder the efficient allocation of financial resources. To ensure financial market stability, serve the real economy, and drive high-quality national economic development, it is essential to explore the impact and economic consequences of the pilot fintech city policy on capital market mispricing.

Many studies have examined the effects of fintech from multiple perspectives, including corporate behavior, industrial structure, and economic development. For example, Zhang Yuxi and Zhao Lili (2015) found that fintech investment significantly supports technological innovation in the short term. Qian Shuitu and Zhang Yu (2017) demonstrated that fintech development has a notable incentive effect on corporate R&D investment. Cheng Xiang et al. (2020) showed that government-level fintech policies provide significant support to firms, improving their competitiveness. Wang Shujuan and Gu Shen (2021) found that fintech significantly promotes high-quality economic development in China. Hu Huanhuan and Liu Chuanming (2021) concluded that the implementation of fintech policies drives the upgrading of the industrial structure. Wang Wenwen et al. (2024) found that pilot fintech policies significantly foster the development of new productive forces in pilot regions. Building upon previous literature, this paper further investigates the impact of pilot fintech city policies on capital market mispricing.

In theory, the development of fintech may help suppress asset mispricing among enterprises. As information transparency improves, investors can more easily access financial and operational information, reducing information asymmetry and enabling more accurate valuation. Song Min et al. (2021) found that regional fintech development mitigates information asymmetry between financial institutions and firms, thereby reducing financing constraints (in terms of quantity) and optimizing credit allocation (in terms of quality), ultimately enhancing total factor productivity. With better information availability, investors can make more rational decisions based on accurate data, reducing irrational trading and thus limiting asset price deviations. Zhang Zongxin and Wang Hailiang (2013) found that investor sentiment significantly affects market volatility and returns. Additionally, fintech enhances market liquidity, improves capital allocation efficiency, and eases financing constraints, allowing firms to secure more stable funding. For instance, Yu Hongwei et al. (2020) found that fintech reduces financing costs and constraints for tech SMEs through diversified tools such as enhanced credit support, IP pledge loans, leasing, subsidies, and equity investment, thereby promoting innovation. Therefore, fintech may help reduce asset mispricing by increasing transparency, optimizing investor behavior, and improving liquidity.

However, the development of fintech, while improving market efficiency, may also exacerbate asset mispricing. Leveraging big data and AI, fintech promotes algorithmic and high-frequency trading, which can increase market volatility and cause asset prices to deviate from fundamentals (Shi Guangwei, 2020). This volatility can amplify investor behavior biases, encouraging herding and short-term speculation. According to noise trading theory, when investors rely on non-fundamental information, asset prices may deviate from intrinsic value (Black, 1986; Delong, 1990). Furthermore, quantitative traders often rely on models rather than fundamentals, resulting in crowded trades and intensified short-term market fluctuations (Chincarini, 2012). High-frequency traders may even manipulate markets through tactics like flash trading and front-running (Cartea & Penalva, 2012), while corporate management may exploit such strategies to interfere with the market.

Given these contrasting mechanisms, the overall impact of fintech on asset mispricing is theoretically ambiguous and thus calls for empirical testing. Using data from A-share listed firms from 2008 to 2022, this paper finds that fintech significantly suppresses corporate asset mispricing. This result remains robust under parallel trend testing, PSM-DID, and placebo tests. Further heterogeneity analysis shows that the effect is more pronounced among firms located in eastern China, non-state-owned enterprises, and firms in cities not designated as environmental protection hubs. Mechanism analysis confirms that fintech does indeed help suppress mispricing by improving transparency, alleviating financing constraints, and optimizing investor behavior.

This paper contributes in several ways. First, it expands the literature on the impact of fintech on asset mispricing. While existing studies mainly explore how fintech affects innovation by promoting R&D (Chen Jianli, 2020), enhancing technological innovation (Li Yuanyuan & Liu Siyu, 2021), and improving innovation efficiency (Zhang Jiayong, 2020), this paper focuses on how fintech affects mispricing by optimizing the information environment and reducing financing constraints. Second, it broadens the research on the determinants of asset mispricing. While previous studies have shown that factors such as the tone of MD&A disclosures or auditor expertise affect mispricing (Wang Shengnian et al., 2018), this study provides a new perspective by examining how fintech influences mispricing through transparency, liquidity, and investor behavior. Third, this research has important practical implications. Asset mispricing may lead to distorted resource allocation and increased market volatility. Since fintech shows promise in curbing such mispricing, further promoting fintech development, enhancing market transparency, and reducing information asymmetry are essential steps toward building a healthy and stable capital market.

The remainder of the paper is organized as follows: Section 2 reviews relevant literature; Section 3 outlines the research hypotheses and empirical design; Section 4 presents empirical results; Section 5 provides additional analyses; and Section 6 concludes.

2. Literature Review

2.1. Research on Fintech

Fintech, which leverages technologies such as big data, artificial intelligence, and blockchain, has provided crucial support for technological innovation. Its deep integration with the financial sector has significantly improved the level of innovation in pilot regions (Ma Lingyuan & Li Xiaomin, 2019). This feature helps optimize resource allocation, promote enterprise R&D activities and technological advancement, enhance innovation capabilities, and provide new development opportunities in competitive markets.

The development of fintech promotes enterprise innovation by optimizing resource allocation and providing financial support for innovation. Tang Wen et al. (2011) pointed out that the implementation of guiding funds for technological innovation in small and medium-sized tech enterprises alleviated their financing difficulties and helped create a multi-channel support system for innovation. Shu Langen (2011) found that the “technology + finance” business platform promoted innovative fintech integration models, achieving win-win cooperation among banks and enterprises and accelerating technological innovation. Li Ruijing (2017) discovered that fintech, through fiscal technology investment and venture capital, provided funding support for small and medium-sized enterprises (SMEs), thereby boosting R&D and innovation. Ma Weimin and Zhang Ranjan (2019) showed that fintech offers strong financial support by linking technology with finance and leveraging developments in data sharing, the sharing economy, and blockchain technology to improve financing efficiency and create more opportunities for innovation.

Enterprise innovation plays a crucial role in driving long-term growth, enhancing market competitiveness, and boosting economic development. Solow (1957) found that innovation is a key driver for maintaining competitive advantages and sustaining economic growth. Lin Yifu (2002) emphasized that innovation activities propel industrial and technological upgrades. Liu Xihuai (2007) found that continuous innovation enables the launch of new products and production techniques, raising the knowledge and technological content of products, reducing costs, and helping enterprises maintain competitiveness in fiercely contested markets. Hong Yinxing (2013) argued that national competitiveness is increasingly reflected through industrial competitiveness, with enterprise innovation as an endogenous growth driver that should be industry-oriented to enhance national strength and support economic development.

2.2. Literature Review on Asset Mispricing

Existing studies show that asset mispricing is a common issue that can lead to resource misallocation, increase the risk of stock price crashes, jeopardize financial stability, and ultimately affect the real economy (Bi Peng & Yang Ge, 2024). Such mispricing prevents market prices from accurately reflecting firms’ intrinsic values, impairing the risk management strategies of listed companies, investors, and regulators (Gao Ya & Liu Chang, 2020). Furthermore, under external information stimuli, investors may exhibit cognitive biases and irrational behavior, causing asset prices to deviate from intrinsic values (You Jiaxing & Wu Jing, 2012).

The rationality of asset pricing significantly affects corporate investment and financing decisions and the efficiency of resource allocation. Research has found that stock overvaluation, via equity financing channels, exacerbates overinvestment (Wang Shengnian et al., 2018). Conversely, when stock prices are undervalued, companies may abandon promising investment projects due to high external financing costs or the inability to raise capital (Zhang Jing & Wang Shengnian, 2016). Moreover, fair market pricing improves corporate governance and operational efficiency, while mispricing can intensify short-termism and speculative behavior.

Further studies show that market conditions and external pressures amplify the effects of mispricing on corporate decisions. For example, stock-based compensation schemes may increase managerial opportunism in earnings management, heighten information asymmetry between investors and firms, and ultimately aggravate asset mispricing (Wang Shengnian & Zhu Yanyan, 2017). Li Qian et al. (2018) found that analysts' optimistic ratings and upgrades can lead to upward asset mispricing. Investor sentiment, the degree of information asymmetry, and positive MD&A (Management Discussion and Analysis) tone also influence market perceptions of asset value, further aggravating mispricing. Additionally, Gao Ya and Liu Chang (2020) noted that managers, by manipulating MD&A tone, can influence investor sentiment and exacerbate information asymmetry, resulting in asset mispricing.

In summary, asset mispricing can lead to inefficient resource allocation, increase market risk, and affect corporate investment and financing decisions. However, current research has not reached a consensus on how fintech pilot policies influence asset mispricing, nor has it sufficiently analyzed the mechanisms through which information transparency, investor behavior, and liquidity in asset allocation affect mispricing. Therefore, this paper explores the impact of fintech pilot programs on enterprise asset pricing from market and policy perspectives, which holds significant theoretical and practical value.

3. Research Hypothesis and Empirical Design

3.1. Research Hypothesis

Existing studies have shown that fintech, by leveraging technologies such as big data, artificial intelligence, and blockchain, enhances the financial market’s information processing capacity and optimizes capital allocation efficiency. As a key initiative aligned with the demands of the times and national strategic priorities, the development of fintech helps promote rational allocation in factor markets and improves the efficiency of financial resource utilization (Li Junxia & Wen Xiaoni, 2019). With strong support from national macro policies, fintech has rapidly developed and become a key driver of innovation. It performs functions such as resource allocation, risk management, information processing, and regulatory oversight (Cheng Haiyan et al., 2020). Under the promotion of the fintech city pilot policy, the degree of information asymmetry between borrowers and lenders has decreased, guiding more credit resources to flow toward small and medium-sized tech enterprises and easing their financing constraints (Ma Lingyuan & You Hang, 2021). This may have significant implications for the pricing mechanism in capital markets.

These impacts are primarily reflected in the optimization of the information environment, which helps reduce firms’ financing costs. The development of financial technology can improve the quality of information disclosure by listed companies and enhance information efficiency in capital markets, thereby reducing pricing deviations caused by information asymmetry (Yang Songling et al., 2021). At the same time, fintech, based on technologies such as artificial intelligence and cloud computing, has expanded the channels through which traditional financial institutions acquire information, further broadened the scope of information sharing, and improved information accuracy (Shen Yue & Guo Pin, 2015; Huang et al., 2018). Moreover, fintech empowers traditional financial institutions by improving bank-enterprise relationships, effectively alleviating problems of information asymmetry and the resulting credit rationing. This not only reduces the average level of financing constraints for enterprises but also enhances the efficiency of credit resource allocation (Song Min et al., 2021).

Studies indicate that pricing deviations in capital markets are often affected by environmental uncertainty and irrational investor behavior, while financing plays a crucial role in the effective functioning of capital markets. Zhang Xiao (2020) found that the margin trading system can help mitigate the impact of asset mispricing on stock price crash risk. Meanwhile, Luo Shan (2023) pointed out that the margin trading mechanism generally facilitates more reasonable asset pricing, enabling stock prices to reflect intrinsic value more closely. Given that the fintech pilot policy can influence market pricing mechanisms by improving the information environment and reducing financing costs, we hypothesize that its implementation may help reduce financing constraints and lower capital costs for enterprises, thereby curbing asset mispricing to some extent. Based on the above analysis, this paper proposes the following hypothesis:

H1: The implementation of the fintech city pilot policy significantly reduces the level of asset mispricing among enterprises.

3.2. Empirical Design

To test whether the fintech pilot policy helps suppress capital mispricing, the following regression model is constructed, based on Zheng Shiming et al. (2020):

$$\mathrm{Misp1}_{i,t} = \beta_0 + \beta_1 \mathrm{Treat\_Post}_{i,t} + \gamma' \mathrm{Control}_{i,t} + \sum \mathrm{Year} + \sum \mathrm{Industry} + \varepsilon_{i,t} \tag{1}$$

3.2.1 Measurement of Capital Mispricing

Drawing on the approach commonly used in existing literature, this study adopts two widely accepted methods in academia to measure the level of capital mispricing. The first method, originally proposed by Berger et al. (1995), has been extensively applied in subsequent research. This approach first estimates the fundamental value of a company based on peer firms within the same industry. Then, by comparing a firm's actual market value with its estimated fundamental value, the degree of mispricing relative to industry peers can be assessed. The calculation formula is as follows:

$$\mathrm{Misp1}_{i,t} = \mathrm{Ln}[\mathrm{Capital}_{i,t}/\mathrm{Imputed}\ (\mathrm{Capital}_{i,t})] = \mathrm{Ln}\ [\mathrm{Capital}_{i,t}/\ (\mathrm{Asset}_i \times \mathrm{Ratio}_i)] \tag{2}$$

Among them, *Capital* refers to the sum of the market value of common equity and the book value of liabilities; *Imputed (Capital)* is the firm's estimated fundamental value; *Asset* represents the total assets of the company; and *Ratio* is the median value of the *Capital-to-Asset* ratio across all firms within the same industry. By substituting the above values into the formula, the degree of mispricing *Misp1* can be calculated.

The second method draws from the study by Rhodes-Kropf et al. (2005), which also measures capital mispricing by comparing a firm's market value to its fundamental value, but the procedure differs in several ways. First, quarterly and industry-specific regressions are performed using the following equation (3) to obtain the regression coefficients for each industry in each quarter: $\{\alpha_{0jt}, \alpha_{1jt}, \alpha_{2jt}, \alpha_{3jt}, \alpha_{4jt}\}$; Next, the average of these regression coefficients across all quarters within the same industry is taken to obtain the industry's estimation model. Then, each firm's specific explanatory variable values are substituted into this model to estimate the firm's fundamental value *V*. Finally, the mispricing level *Misp2* is calculated using the formula: *ln (M / V)*:

$$\mathrm{LnM}_{i,t} = \alpha_{0jt} + \alpha_{1jt}\mathrm{LnB}_{i,t} + \alpha_{2jt}\mathrm{Ln(NI)}^{+}_{i,t} + \alpha_{3jt}\mathrm{I}_{(<0)}\mathrm{Ln(NI)}^{+}_{i,t} + \alpha_{4jt}\mathrm{Lev}_{i,t} + \varepsilon_{i,t} \tag{3}$$

Where: *M* is the market value of the firm, calculated as the sum of the book value of non-tradable shares and the market value of tradable shares; *B* represents the total assets of the firm; $(NI)^+$ is the absolute value of the firm's net income; $I_{(<0)}$ is a dummy variable that equals 1 if the firm's net income is negative $NI < 0$, and 0 otherwise; *Lev* is the leverage ratio, calculated as the ratio of total liabilities to total assets; *V* is the estimated fundamental value of the firm.

3.2.2 Measurement of the Sci-Tech Finance Pilot Policy

Following the approach of Zheng Shiming et al. (2020), this paper adopts a widely accepted method in academic research to measure the implementation of the sci-tech finance pilot policy. Specifically, we define a policy dummy variable, *policy*, which takes the value of 1 if a sample city is included in the pilot program and the observation period falls within the implementation phase of the policy; otherwise, *policy = 0*, indicating that the city was either not included in the pilot program or the observation occurs before the policy was implemented. This paper first identifies the cities covered by the policies implemented in 2011 and 2016. Then, we construct a *Treat_Post* variable as follows: if a firm is located in a city that is part of the treatment group and the observation year is after the policy implementation year, then *Treat_Post = 1*; otherwise, *Treat_Post = 0*.

3.2.3 Measurement of Control Variables

Control includes a series of control variables such as: total assets (*Size*), asset-liability ratio (*Lev*), return on total assets (*ROA*), total asset turnover (*ATO*), cash flow ratio (*Cashflow*), accounts receivable ratio (*REC*), fixed assets ratio (*FIXED*), total asset growth rate (*AssetGrowth*), inventory ratio (*INV*).

We control for both $\sum \mathrm{Year}$ and $\sum \mathrm{Industry}$fixed effects in the regression models. To account for potential cross-sectional correlation, all regressions adopt standard errors clustered at the firm level. Detailed definitions are provided in Table 1.

Table 1 Variable Definitions and Construction

Variable Synbol	Variable Name	Definitions and Construction
Misp1	Asset Mispricing	See model for definition
Treat_Post	FinTech Pilot	Equals 1 if the city where the company is located is included in the policy pilot group and the year is after policy implementation; 0 otherwise
Size	Total Assets	Total assets at the end of the year
Lev	Leverage Ratio	Ratio of total liabilities to total assets
ROA	Return on Assets	Ratio of net profit to total assets
ATO	Asset Turnover Ratio	Ratio of operating revenue to total assets
Cashflow	Cash Flow Ratio	Ratio of cash flow from operating activities to current liabilities
REC	Accounts Receivable Ratio	Ratio of accounts receivable to operating revenue
FIXED	Fixed Assets Ratio	Ratio of fixed assets to total assets
AssetGrowth	Asset Growth Rate	Current total assets divided by previous period total assets, minus 1
INV	Inventory Ratio	Ratio of inventory to total assets

3.3. Data Source

We select A-share companies listed on the Shanghai and Shenzhen Stock Exchanges from 2008 to 2022 as the research sample. All data are obtained from the CSMAR database. Based on the needs of the research design, the following sample selection criteria are applied: (1) financial companies such as banks and insurance firms are excluded; (2) companies with missing media coverage data are excluded; (3) companies with incomplete trading or financial data are also excluded. In addition, to reduce the impact of extreme values and ensure the robustness of the results, we perform a 1% winsorization at both ends of the distribution, yielding a final sample of 24,562 observations.

3.4. Descriptive Statistics

Table 2 presents the descriptive statistics of the control variables and dependent variables used in this paper, including the number of observations, mean, standard deviation, minimum, and maximum values. Specifically, the asset mispricing level measured using the text analysis method shows a minimum value of -6.907, a maximum of 8.869, a mean of 0.106, and a standard deviation of 0.495, indicating significant variation in mispricing levels among firms. This suggests that market prices often deviate from firms' intrinsic values. In an efficient pricing mechanism, stock prices should align closely with intrinsic values, and the mean of mispricing proxies should be approximately zero (You Jiaxing & Wu Jing, 2012). However, the actual situation deviates from this expectation. For example, the mean of the Misp1 variable is 0.106, implying that asset mispricing has been a persistent issue in China's stock market.

Table 2 Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
Misp1	54,173	0.106	0.495	-6.907	8.869
Treat_Post	46,476	0.567	0.496	0	1
Size	46,476	22.140	1.300	19.410	26.440
Lev	46,476	0.416	0.208	0.027	0.925
ROA	46,474	0.041	0.067	-0.375	0.255
ATO	46,470	0.647	0.438	0.057	2.918
Cashflow	46,476	0.047	0.070	-0.226	0.283
REC	46,355	0.121	0.102	0	0.506
INV	46,127	0.140	0.127	0	0.760
FIXED	46,476	0.208	0.158	0.002	0.765
AssetGrowth	46,450	3.542	628.500	-1.445	134,607

4. Empirical Results

4.1. Baseline Regression Analysis

To examine the impact of the two rounds of the Fintech pilot policies on asset mispricing from 2008 to 2022, we conducted baseline regressions. The regression results are shown in Table 3. Column (1) presents the regression results without control variables or fixed effects. Column (2) shows the regression results without control variables. Column (3) reports the regression results without fixed effects. Column (4) includes both control variables and fixed effects. The effects observed in all four cases are generally consistent. The results show that the coefficient of the core explanatory variable (Treat_Post) is negative and statistically significant at the 5% level. This suggests that the Fintech policy has a specific effect, with the level of asset mispricing being more significantly suppressed in pilot cities compared to non-pilot cities. For example, in column (4), the dependent variable is the composite measure of asset mispricing, Misp1. The regression coefficient for the Fintech city pilot is -0.019, indicating that the average Misp1 in the experimental group is 0.019 lower than in the control group. Media sentiment has a significant impact on the level of asset mispricing, and this empirical result supports the research hypothesis.

Table 3 Baseline Regression Results

	(1)	(2)	(3)	(4)
VARIABLES	Misp1	Misp1	Misp1	Misp1
Treat_Post	-0.073***	-0.030***	-0.027***	-0.019**
	(-8.091)	(-2.805)	(-3.423)	(-2.123)
Size			-0.142***	-0.165***
			(-30.531)	(-31.703)
Lev			0.124***	0.092***
			(4.423)	(3.244)
ROA			1.269***	1.302***
			(17.059)	(17.150)
ATO			-0.026***	0.021**
			(-2.717)	(1.962)
Cashflow			0.408***	0.378***
			(9.046)	(8.525)
REC			-0.305***	-0.300***
			(-6.967)	(-6.518)
FIXED			-0.111***	-0.112***
			(-4.003)	(-3.877)
AssetGrowth			0.042***	0.024***
			(5.320)	(3.111)
INV			-0.042	-0.060
			(-1.273)	(-1.441)
Constant	0.180***	0.340***	3.264***	3.789***
	(26.517)	(8.942)	(31.945)	(33.804)
Observations	35,118	35,118	35,118	35,118
R-squared	0.007	0.129	0.196	0.340
Industry FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Values in parentheses are t-statistics. The same notation applies to all subsequent tables.

4.2. Robustness Checks

4.2.1 Parallel Trend Test

The application of the Difference-in-Differences (DID) method must satisfy a key prerequisite: in the absence of policy shocks, the time trends of the treatment and control groups should be parallel and should not exhibit systematic differences over time. Therefore, this paper conducts a parallel trend test based on regression results by interacting the treatment and time dummy variables to examine whether the coefficients are statistically significant.

Since DID estimates may suffer from bias (Goodman-Bacon, 2021; Sun and Abraham, 2021), this study adopts the approach proposed by Xu Yueqian et al. (2021) to construct the following regression model.

$$\mathrm{Misp1}_{i,t} = \varphi_0 + \sum_{k\geq -4, k\neq -1}^{5} \varphi_k \, D_{i,t}^{k} + \mu \mathrm{Control}_{i,t} + \sum \mathrm{Year} + \sum \mathrm{Industry} + \varepsilon_{it} \qquad (4)$$

In the above model, serves as the dependent variable, representing the level of asset mispricing. The dummy variable $D_{i,t}^{k}$ indicate the observation values for city i in the k years before, the year of, and the t years after the implementation of the fintech pilot policy. For cities that did not implement the policy, the dummy variables are all set to 0. To ensure sufficient comparison periods before and after the policy implementation, we set k = 4 and t = 5. φ_k reflect the differences and trends in asset mispricing between cities that implemented the fintech pilot policy and those that did not during the k year after policy implementation. The model also includes an intercept term φ_0, a vector of control variables with an estimated coefficient μ, and other variables consistent with those defined in Equation (1).

As shown in Figure 1, in the years prior to the policy implementation, all estimated coefficients are statistically insignificant and close to 0, suggesting no significant difference between the treatment and control groups—thereby satisfying the parallel trend assumption. However, after the implementation of the policy, significant changes begin to appear. The coefficients for asset mispricing become significant starting from the year of policy implementation, remain significant in the first year after implementation, become insignificant in the second and third years, and regain significance in the fifth year. This suggests that the policy has a lagged and nonlinear effect on asset mispricing. These results support the validity of the parallel trend assumption, reinforcing the robustness of the study's conclusions.

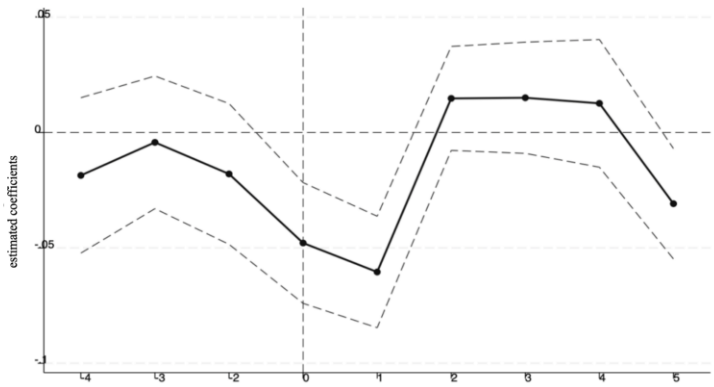

Fig. 1 Parallel Trend Test

4.2.2 PSM-DID

In addition, this study conducts a robustness check using the Propensity Score Matching Difference-in-Differences (PSM-DID) method. The specific steps are as follows: we first use the control variables mentioned above to perform a Logit regression to calculate the propensity scores. Then, a 1:1 nearest-neighbor matching rule is applied to match the treatment and control samples. Finally, we calculate the average treatment effect. The results of the PSM-DID regression in Table 4 show that the explanatory variable *Treat_Post* has a significant negative effect on the dependent variable *Misp1* at the 10% significance level. The model also shows a good fit, with an R-squared of

0.334. This indicates that the fintech pilot policy significantly reduced the level of asset mispricing in firms located in the matched pilot regions. These findings are consistent with the baseline DID results, suggesting that the conclusions of the DID model are robust.

Table. 4 PSM-DID Test

	(1)	(2)	(3)	(4)
VARIABLES	Misp1	Misp1	Misp1	Misp1
Treat_Post	-0.060***	-0.021*	-0.026***	-0.017*
	(-6.537)	(-1.885)	(-3.244)	(-1.942)
Size			-0.141***	-0.162***
			(-28.455)	(-30.132)
Lev			0.130***	0.091***
			(4.354)	(3.052)
ROA			1.274***	1.307***
			(16.425)	(16.537)
ATO			-0.027***	0.017
			(-2.902)	(1.624)
Cashflow			0.414***	0.387***
			(8.595)	(8.177)
REC			-0.291***	-0.284***
			(-6.524)	(-6.096)
FIXED			-0.109***	-0.110***
			(-3.632)	(-3.540)
AssetGrowth			0.049***	0.031***
			(5.784)	(3.687)
INV			-0.048	-0.066
			(-1.406)	(-1.540)
Constant	0.168***	0.321***	3.218***	3.713***
	(23.542)	(7.822)	(29.821)	(31.808)
Observations	31,272	31,272	31,272	31,272
R-squared	0.005	0.126	0.192	0.334
Industry FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES

4.2.3 Placebo Test

To verify whether the pilot policy of technology and finance truly caused changes in capital market mispricing, this study conducts a placebo test by randomly reassigning the treatment (pilot) and control groups for the variable *Treat_Post*. This process simulates a scenario where the impact of the pilot policy on capital market mispricing is random. Specifically, a random sample is drawn from the original dataset to simulate “treatment” and “control” groups, with the sample sizes equal to those of the actual groups. This process is repeated 500 times, yielding 500 regression coefficients. As shown in Figure 2, the distribution of the *Treat_Post* coefficients centers closely around zero and is mostly greater than the actual estimated coefficient of -0.019. This finding indirectly confirms that the measurement error in the actual treatment group is within a tolerable range, and the statistical significance of the original coefficient is robust.

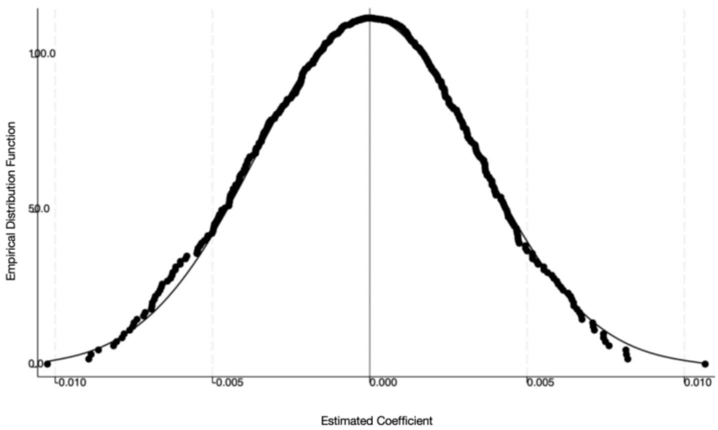

Fig. 2 Placebo Test

5. Further Analysis

5.1. Heterogeneity Analysis

5.1.1 Regional Heterogeneity

Based on the geographical heterogeneity of cities, this study divides the sample cities into three regions—eastern, central, and western—according to the provinces they belong to, and conducts separate regression analyses for each subgroup. Table 5 reports the regression results on the impact of the sci-tech finance pilot policy on corporate asset mispricing in different regions. The coefficients of the sci-tech finance policy are negative across the eastern, central, and western regions, with the policy effect being most significant in the eastern region, followed by the western region, while the effect in the central region is not statistically significant. A possible explanation is that the eastern region has notable advantages over the central and western regions in terms of infrastructure, technological R&D, and talent reserves. These advantages enable the eastern region to better implement the sci-tech finance policy, thereby significantly improving the pricing efficiency of the capital market.

Table 5 Regional Heterogeneity

	(1)	(2)	(3)
Variable \ Group	eastern	central	western
Treat_Post	-0.018***	-0.007	-0.021*
	(-3.238)	(-0.903)	(-1.921)
Size	-0.154***	-0.198***	-0.189***
	(-67.127)	(-54.521)	(-38.274)
Lev	0.090***	0.122***	0.075**
	(5.514)	(5.073)	(2.299)
ROA	1.312***	1.322***	1.199***
	(28.059)	(17.848)	(12.192)
ATO	0.010*	0.037***	0.046***
	(1.646)	(3.952)	(3.953)
Cashflow	0.379***	0.437***	0.546***
	(9.883)	(7.275)	(6.954)
REC	-0.255***	-0.382***	-0.247***
	(-9.264)	(-8.643)	(-4.120)
FIXED	-0.108***	-0.131***	-0.085**
	(-5.588)	(-4.933)	(-2.375)
AssetGrowth	0.030***	0.012	0.009
	(4.725)	(1.366)	(0.791)
INV	-0.125***	0.098***	0.221***
	(-5.349)	(2.579)	(4.282)
Constant	3.581***	4.402***	4.219***
	(67.077)	(56.808)	(39.536)
Observations	24,706	10,412	5,954
R-squared	0.334	0.376	0.377
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

5.1.2 Ownership Heterogeneit

Based on the nature of property rights, firms are classified into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs), with SOEs coded as 1 and non-SOEs as 0 in a dummy variable. Separate regressions were conducted for each ownership type. Table 6 reports the regression results on the impact of the Sci-Tech Finance Pilot Policy on asset mispricing across different ownership groups. In the SOE group, the estimated coefficient is -0.010, but it is not statistically significant. In contrast, the estimated coefficient for the non-SOE group is -0.019, which is statistically significant at the 10% level. This indicates that the pilot policy has a stronger suppressing effect on asset mispricing among non-SOEs compared to SOEs. The likely reason lies in the differences in financing capacity and market environment between SOEs and non-SOEs. Generally, SOEs enjoy higher credit ratings and easier access to loans from financial institutions, leading to lower financing constraints and costs. As a result, SOEs can quickly obtain sufficient financial support after the implementation of the policy, which weakens the policy's marginal impact on improving capital market pricing efficiency. In contrast, non-SOEs—especially small and medium-sized tech enterprises—often face severe financing difficulties due to "ownership discrimination" and weaker market positions. This is particularly evident in innovation-related financing (Wang Chunchao, 2017). The sci-tech finance pilot policy, by offering government subsidies, tax incentives, and other supportive measures, effectively alleviates financing constraints for these firms, reduces their financing costs, and promotes capital inflow. This significantly improves the financing environment for non-SOEs, enhances their innovation and technological progress, and more effectively curbs capital market mispricing, thereby improving market efficiency and corporate competitiveness.

Table 6 Ownership Heterogeneit

	(1)	(2)
Variable \ Group	*SOEs*	*non-SOEs*
Treat_Post	-0.010	-0.019*
	(-0.652)	(-1.740)
Size	-0.164***	-0.168***
	(-24.978)	(-21.634)
Lev	-0.074*	0.175***
	(-1.689)	(4.806)
ROA	1.442***	1.260***
	(9.605)	(14.716)
ATO	0.022	0.007
	(1.369)	(0.454)
Cashflow	0.187***	0.489***
	(2.854)	(8.481)
REC	-0.252***	-0.302***
	(-3.467)	(-5.359)
FIXED	-0.121***	-0.080**
	(-2.848)	(-2.016)
AssetGrowth	-0.006	0.042***
	(-0.690)	(3.905)
INV	0.005	-0.119**
	(0.079)	(-2.279)
Constant	3.833***	3.834***
	(26.974)	(22.796)
Observations	12,852	22,266
R-squared	0.416	0.313
Industry FE	YES	YES
Year FE	YES	YES

5.1.3 Differences Between Key Environmental Protection Cities and Others

Key environmental protection cities implement stricter regulatory policies, requiring enterprises to adopt higher environmental standards and promote cleaner production technologies and processes. These cities also utilize sci-tech finance policy tools to attract more social capital into the environmental sector, encouraging firms to implement eco-friendly measures such as carbon and pollution reduction. This not only enhances production efficiency and resource utilization but also fosters the development of new productive forces. Additionally, improvements in environmental quality help attract high-end talent and innovative enterprises, creating a favorable environment for innovation and living, thereby supporting the growth of new productive forces (Wang Wenwen et al., 2024). Based on the *National Environmental Protection "11th Five-Year Plan"* issued by the State Council, the sample cities were divided into key environmental protection cities and non-key cities. Group regressions were conducted accordingly. Table 7 reports the regression results on the impact of the sci-tech finance pilot policy on asset mispricing across the two groups. In key environmental protection cities, the estimated coefficient is -0.018, while in non-key cities, the coefficient is -0.068. Both coefficients are statistically significant at the 1% level. This indicates that the sci-tech finance pilot policy has a stronger suppressing effect on asset mispricing in non-key environmental protection cities than in key ones. One possible explanation is that enterprises in non-key cities rely more heavily on external policy incentives. The sci-tech finance pilot policy provides these firms with greater access to capital and innovation opportunities, making it more effective in curbing asset mispricing. In contrast, enterprises in key environmental protection cities are already subject to strict environmental regulations and enjoy a relatively high level of pricing transparency, resulting in a milder policy effect. Moreover, firms in non-key cities often face fiercer market competition and thus have a more urgent need to enhance their competitiveness through technological innovation and financial support, which in turn promotes more rational asset pricing. For enterprises in key cities, the marginal benefits of the policy are less pronounced due to pre-existing regulatory pressures. Lastly, local governments in non-key cities may be more proactive in implementing the policy, compensating for delays or deficiencies in environmental regulation and amplifying the policy's effectiveness.

Table 7 Differences Between Key Environmental Protection Cities and Others

	(1)	(2)
Variable \ Group	key cities	non-key cities
Treat_Post	-0.018***	-0.068***
	(-3.462)	(-6.233)
Size	-0.163***	-0.176***
	(-77.499)	(-36.270)
Lev	0.100***	0.061**
	(6.602)	(2.065)
ROA	1.364***	1.093***
	(30.546)	(12.622)
ATO	0.027***	0.001
	(4.708)	(0.056)
Cashflow	0.356***	0.465***
	(9.802)	(6.522)
REC	-0.325***	-0.188***
	(-12.703)	(-3.265)
FIXED	-0.106***	-0.086**
	(-6.034)	(-2.507)
AssetGrowth	0.021***	0.038***
	(3.567)	(3.220)
INV	-0.091***	0.064
	(-4.164)	(1.355)
Constant	3.732***	4.043***
	(76.944)	(38.837)
Observations	27,966	7,152
R-squared	0.344	0.339
Industry FE	YES	YES
Year FE	YES	YES

5.2. Mechanism Test

The enhancement of information transparency, increased resource allocation liquidity, and optimized investor behavior jointly influence the corporate asset pricing process, contributing to the reduction of asset mispricing. The improvement in information transparency helps alleviate information asymmetry in the market, enabling investors to more accurately assess the value of enterprises and reduce price deviations caused by a lack of or distorted information. Smoother financing channels and higher market liquidity optimize capital allocation efficiency, directing funds more effectively toward companies with growth potential and robust operational capabilities, thus enhancing the market's ability to rationally price enterprise value. Additionally, the improved market environment adjusts investor decision-making patterns, with more abundant channels for acquiring information, a higher proportion of rational investors, and reduced herd behavior and short-term speculation. As a result, asset prices are more driven by fundamental factors of the company rather than market sentiment and short-term noise. These factors interact to suppress market noise and short-term fluctuations, leading to more rational asset pricing and, consequently, a reduction in asset mispricing.

5.2.1 Information Transparency:

This paper posits that one pathway through which the sci-tech finance pilot policy suppresses asset mispricing is by improving information transparency. Column (1) of Table 8 shows the mechanism test results for overall information transparency. It is evident that the coefficient of the sci-tech finance policy is significantly positive at the 1% level. This indicates that the sci-tech finance policy can enhance the information transparency of enterprises in pilot cities, thereby reducing asset mispricing. Hence, hypothesis H1 is validated.

5.2.2 Investor Behavior:

This paper suggests that the sci-tech finance pilot policy enables investors to better understand market dynamics, thus suppressing the asset mispricing level of companies. Column (2) of Table 8 presents the mechanism test results for the composite index of investor sentiment. The coefficient of the sci-tech finance policy is significantly positive at the 10% level. This implies that the sci-tech finance pilot policy can optimize investor behavior, reducing mispricing in the capital market. Consequently, hypothesis H1 is validated.

5.2.3 Market Liquidity:

This paper also argues that the sci-tech finance pilot policy suppresses asset mispricing by improving market liquidity. Column (3) of Table 8 shows the mechanism test results for the daily turnover rate of tradable shares. The coefficient of the sci-tech finance policy is significantly positive at the 5% level. This suggests that the sci-tech finance pilot policy can reduce capital market mispricing by enhancing market liquidity. Therefore, hypothesis H1 is verified.

Table 8 Mechanism Test

	(1)	(2)	(3)
VARIABLES	TIT	IS	DSIC
Treat_Post	0.114***	0.019*	0.065**
	(3.701)	(1.950)	(2.091)
Size	0.004	0.037***	-0.416***
	(0.269)	(8.550)	(-32.440)
Lev	-1.060***	-0.266***	0.675***
	(-11.079)	(-9.340)	(7.254)
ROA	6.932***	-0.994***	-1.648***
	(25.039)	(-11.504)	(-6.896)
ATO	0.005	0.016	-0.094***
	(0.143)	(1.547)	(-2.808)
Cashflow	-6.161***	-0.178***	-0.307*
	(-25.749)	(-3.061)	(-1.761)
REC	1.424***	0.145***	0.302*
	(8.225)	(2.803)	(1.728)
FIXED	-0.357***	0.267***	-0.007
	(-3.238)	(8.657)	(-0.075)
AssetGrowth	0.003	0.048***	0.332***
	(0.076)	(4.737)	(11.297)
INV	1.939***	0.059	-0.044
	(14.177)	(1.448)	(-0.366)
Constant	5.455***	-1.452***	12.647***
	(17.975)	(-15.615)	(42.717)
Observations	24,562	24,562	24,562
R-squared	0.118	0.454	0.306
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

6. Conclusion

This paper takes the long-standing anomaly in capital markets—asset mispricing—as the entry point and conducts an in-depth analysis of the mechanism through which the sci-tech finance pilot policy influences asset pricing. Based on empirical tests using 24,562 annual observations of A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2008 to 2022, the findings reveal that the policy significantly alleviates asset mispricing, though the effects vary depending on region, ownership type, and industry characteristics.

Specifically, the empirical analysis shows that the policy's impact is more pronounced in eastern regions, non-state-owned enterprises, and non-key environmental protection cities. This may be attributed to the better-developed sci-tech financial infrastructure in eastern regions, where the policy more effectively channels financial resources into innovative enterprises, enhances the market information environment, reduces information asymmetry, and thereby improves pricing efficiency. Non-state-owned enterprises, often facing tighter financing constraints, benefit from the policy through improved access to funding and reduced capital costs, helping to resolve capital mismatches and enabling more accurate value assessments by the market. Furthermore, in non-key environmental protection cities, relatively looser regulatory pressures allow firms to allocate sci-tech financial resources more freely to productive investments, which promotes more rational market pricing.

Given the regional and firm-level heterogeneity in the development of sci-tech finance, and based on this paper's findings on its effectiveness in reducing asset mispricing, several policy recommendations are proposed: 1. Enhance policy implementation in underdeveloped regions: Increase the reach and intensity of sci-tech financial policies in central and western areas to reduce regional disparities in capital market pricing efficiency. This could be achieved through fiscal subsidies, tax incentives, and preferential credit policies, encouraging financial institutions to allocate more sci-tech financial resources to the western regions. 2. Improve support systems for non-state-owned enterprises: Address their financing difficulties by enhancing the sci-tech finance ecosystem. Policymakers should guide banks, venture capital firms, and other institutions to increase credit and equity support for these enterprises, while leveraging fintech tools to improve credit assessment capabilities and lower financing costs. This would help correct market mispricing associated with financing constraints. 3. Refine regulatory policies based on industry characteristics: Tailor sci-tech financial policy to different industries' needs to ensure that resources truly support technological innovation and rational valuation. This would help prevent the inefficient use of funds or the formation of market bubbles, thereby maintaining a healthier financial ecosystem. These conclusions provide theoretical and empirical support for optimizing the design and implementation of sci-tech finance policies, ultimately promoting high-quality development of capital markets.

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