Fintech Pilot Programs and Digital Innovation: Evidence from Quasi-Natural Experiments in China

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Abstract

The current study examines whether government-led digital finance initiatives promote firm-level digital innovation by leveraging the staggered rollout of China's Fintech pilot programs as quasi-natural experiments. Our dataset comprises 26,746 firm-year observations of A-share listed companies from 2009 to 2023. To measure innovation, we develop a text-based indicator derived from the frequency of digital-related keywords in the annual reports of the listed firms. Employing a multi-period difference-in-differences design, we find that designation as a pilot zone increases digital innovation intensity by 0.8225 per thousand report words. These results remain robust across parallel, propensity score matching, placebo, and robustness tests. Mediation analysis reveals that the part of the effect is attributable to increased R&D intensity, with the program raising the average R&D-to-sales ratio by 0.24 percentage points. Moreover, program effect is stronger among high-tech firms and those located in Central and Western China, regions characterized by relatively weaker financial and digital infrastructure.

Key Words: Difference-in-differences; Fintech pilot programs; digital innovation; R&D investments; firm heterogeneity.

JEL Classifications: G18, G28, G38, O31, O32, O38, O53, P42.

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1 Introduction

China's digital finance sector has experienced rapid growth. In the fourth quarter of 2024, non-bank payment institutions processed 83.6 trillion RMB in online payments—an amount surpassing the nation's total GDP for that quarter. At the individual level, the adoption of digital tools is widespread. According to the *EY Global Fintech Adoption Index 2019*, 87% of digitally active Chinese consumers used at least one Fintech service (Ernst & Young(EY) , 2019). Fintech facilitates easier access to credit for businesses, reduces transaction costs, and accelerates the sharing of financial information. These advantages are particularly critical for small and medium-sized enterprises (SMEs), enabling firms without substantial asset bases to pursue innovation opportunities that were previously unattainable.

A growing body of firm-level studies supports the positive impact of Fintech on innovation. For instance, Howell (2016) investigates China's 2004 value-added tax reform and finds that easing liquidity constraints enables firms to increase the sales of new products and processes, although it does not significantly affect R&D expenditure. Further evidence is provided by Ding, Gu, and Peng (2022), who construct a Fintech index for 331 Chinese cities and show that stronger digital finance ecosystems are associated with increased patent applications and higher R&D investment, particularly among financially constrained firms. Similar patterns are observed internationally. According to the World Bank's *Global Findex* report, the expansion of digital finance has made it easier for individuals to save, borrow, and make payments (Demirgüç-Kunt, Klapper, Singer, Ansar, and Hess, 2018). In Kenya, mobile money services have reduced the cost of risk-sharing (Jack and Suri, 2014), facilitated the growth of small businesses, and contributed to long-term poverty reduction (Suri and Jack, 2016). Collectively, these studies highlight Fintech as a decentralized enabler of firm-level innovation.

Nevertheless, three key limitations persist in the existing literature. First, most empirical studies conceptualize Fintech primarily as a private-sector phenomenon, providing limited evidence on whether government-led initiatives can effectively translate policy objectives into meaningful innovation outcomes—a question of particular relevance for developing and transitional economies. Second, the literature largely concentrates on patent-based indicators, thereby neglecting broader dimensions of digital transformation, such as the adoption of smart manufacturing technologies, the launch of platform-based services, and the integration of data-driven business models. Third, the mechanisms through which Fintech policies influence firms remain insufficiently explored. In particular, it is unclear whether these policies operate solely by easing external financing constraints or also by encouraging firms to reallocate internal resources toward R&D, digital competencies, and other intangible assets.

The Fintech Pilot Program is a national initiative jointly launched by the Ministry of Science and Technology (MOST), the People's Bank of China, and multiple financial regulatory authorities to promote the integration of science, technology, and finance. The program's overarching goals are to ease financing constraints for technology-oriented enterprises, strengthen the interaction between technological innovation and financial capital, and foster innovation-driven growth. Although the policy documents frequently refer to "technology-based SMEs," the design is not SME-exclusive but broadly targets innovative entities such as high-tech firms and strategically emerging industries. Six major mechanisms characterize its implementation: (i) fiscal guidance and venture capital funds that leverage private investment (e.g., Jiangsu's Emerging Industry Venture Capital Guidance Fund with an 8.6-fold leverage effect); (ii) bank credit and risk-sharing mechanisms providing interest subsidies and guarantees for innovative firms (e.g., the Suke Loan scheme); (iii) intellectual property (IP) pledge financing and technology insurance to mitigate credit risk; (iv) technology–finance service platforms that reduce information asymmetry between firms and financial institutions; (v) multi-tier capital market support through regional equity exchanges and innovation boards such as ChiNext and STAR; and (vi) loan–investment linkage models combining equity participation with credit financing. Together, these instruments constitute a comprehensive technology–finance ecosystem that alleviates financing frictions, reduces innovation risks, and accelerates firms' digital transformation. To address these gaps, the present study examines the impact of government-led Fintech initiatives, with a specific focus on China's Fintech pilot programs. Launched initially in 2011 and expanded in 2016, these programs aim to promote corporate digital innovation. Jointly introduced by the Ministry of Science and Technology, the People's Bank of China, and various sectoral financial regulators, the policy designates selected national high-tech zones, innovation demonstration zones, and pilot cities as "technology–finance pilot areas." Within these areas, a comprehensive package of policy instruments is deployed to support innovation. Importantly, the selection of pilot areas was exogenous to local firm-level outcomes. The staggered rollout of the policy thus offers quasi-natural experiments that lend themselves well to a difference-in-differences (DID) estimation strategy. Following Ma and Li (2019) and Shen, Tan, and Yang (2022), we construct treatment indicators based on the timing of policy implementation and the geographic inclusion of each city in the program. Importantly, the selection of pilot areas was exogenous to local firm outcomes. The staggered rollout of the policy, therefore, provides a quasi-natural experiment suitable for difference-in-differences estimation. We follow the definitions of Ma and Li (2019) and Shen et al. (2022) to construct treatment indicators based on the timing and geographic inclusion of each city in the program.

To capture digital innovation, we develop a novel text-based indicator using an unbalanced panel of 26,746 firm-year observations from 2009 to 2023. For each firm-year, digital innovation is measured by analyzing the content of firms' annual reports. The indicator is constructed from a dictionary of 99 keywords related to product, process, and business-model innovations. This dictionary is expanded using a machine learning technique to ensure comprehensive coverage. We then calculate the frequency of these keywords and normalize it by the total word count of each report (expressed per mille). This approach follows Zheng and Zhuang (2024), who recommend measuring digital innovation through corporate disclosures rather than relying solely on patent data.

The DID framework employed in this study is designed to estimate the impact of Fintech pilot programs on digital innovation. It incorporates firm fixed effects and year fixed effects to control for time-invariant firm characteristics and common temporal shocks. To strengthen identification, we supplement the baseline DID with several robustness checks, including a parallel trends test to validate the DID assumptions, propensity-score matching to address selection bias, placebo tests to rule out spurious effects, and additional robustness analyses. Our empirical approach builds on Ding et al. (2022), who investigate how Fintech development fosters firm innovation by alleviating financial constraints.

Three key findings emerge from the analysis. First, the Fintech pilot designation increases the frequency of digital innovation keywords by 0.8225 per mille of total annual report text, with this effect remaining robust across various alternative model specifications. Second, mediation analysis reveals that part of the total effect is driven by increased R&D intensity, as the program raises the average R&D-to-sales ratio. This suggests that internal strategic investment is a critical channel through which the programs foster innovation. Third, the effect is significantly stronger among high-tech firms and those located in China's Central and Western regions, indicating that government-led Fintech initiatives may help mitigate both technological and regional disparities.

This study contributes to the literature across several dimensions. First, it shifts the focus from market-driven dynamics to government-led digital finance interventions, enriching discussions on the public provision of innovation infrastructure. Second, it identifies R&D intensity as a key mechanism through which external Fintech ecosystems affect firms' internal resource allocation, thereby extending resource-based perspectives on innovation. Third, it introduces a scalable, text-based metric that captures multidimensional digital transformation beyond traditional patent measures. Fourth, by revealing heterogeneous policy impacts, the study provides valuable insights for tailoring digital finance programs to specific firm characteristics and regional contexts, promoting inclusive and balanced digital development.

The remainder of this paper is organized as follows. In Section 2, we review the development of Fintech pilot policies in China and develop our theoretical hypotheses. Section 3 describes the empirical strategy, including the regression specifications, variable construction, and data sources. In Section 4, we present the empirical results. Finally, Section 5 concludes the paper and discusses policy implications and limitations.

2 Literature Review and Hypotheses

In this section, we review the prior literature and address key hypotheses for empirical investigations. In particular, we aim to provide causal evidence on how government-led Fintech programs influence digital innovation among firms.

2.1 Fintech Pilot Programs and Corporate Digital Innovation

Government-led Fintech pilot programs are institutional interventions designed to reduce barriers to innovation and foster digital upgrading among firms in China. Firms often face high fixed costs and uncertainty when pursuing innovation, particularly in regions with weaker financial infrastructures. Fintech pilot programs introduce tools such as fiscal subsidies, regulatory sandboxes, public data platforms, and access to capital markets.[1] These instruments lower innovation costs and enhance expected returns from digital investment, as noted by Ma and Li (2019) and Shen et al. (2022).

The endogenous growth theory provides an environment for digital innovation. Romer (1990) and Aghion, Bloom, Blundell, Griffith, and Howitt (2005) provide conditions for firms to invest in innovation. When the marginal benefit of digital innovation exceeds the marginal cost, firms choose their optimal level of investment to maximize the expected benefit. Here, as Hall and Lerner (2010) demonstrate, Fintech programs can improve the expected benefit or reduce the cost, so that firms can invest in digital innovation more easily. For example, they can make it straightforward to access financial and information resources, or they can alleviate financing constraints.

In the current study, the main hypothesis posited by the endogenous growth theory is as follows:

$\mathscr{H}_1$: Fintech pilot programs have a significantly positive impact on firms' digital innovation.

We test this hypothesis using the empirical data collected from Chinese enterprises.

[1] The Fintech pilot programs were launched with the following objectives: (i) restructuring public science and technology funding by integrating non-repayable grants, interest subsidies, risk-compensation funds, and tax incentives to attract private capital for early-stage innovation; (ii) expanding credit access for technology-based small and medium-sized enterprises by encouraging banks to utilize expert evaluation networks, establish specialized tech-finance branches, support small-loan companies, and offer intellectual property–backed lending; (iii) enhancing access to capital markets through support for over-the-counter share transfers, SME bond issuance, and public–private co-investments in venture funds; (iv) developing technology-related insurance products, including premium subsidies for first-use equipment and financing-supportive insurance instruments; (v) building technology-finance service platforms, incubators, and credit rating systems that integrate public data with financial information; and (vi) organizing thematic activities such as innovation contests, roadshows, and training sessions to connect firms with financial institutions.

2.2 R&D as a Transmission Mechanism

One of the biggest resources for firm innovation stems from R&D investment. Fintech programs may influence firm innovation by strengthening internal capabilities, particularly through R&D investment. In the prior literature, different theories discuss the interrelationship between R&D activities and firms' innovation. We discuss the prior literature on the relationship and draw the hypothesis of interest.

First, under the theory of technological progress, R&D investment are essential for firms to accumulate and upgrade their technological capabilities. Through sustained R&D activities, firms acquire new knowledge and integrate existing knowledge both explicitly (e.g., patents, technical documents) and tacitly (e.g., professional know-how, experiential skills). This accumulation strengthens firms' technological ground and enables a deeper understanding of new technologies, providing fertile ground for digital innovation. That is, R&D activities facilitate the creation of technology platforms that serve as an incubator for digital innovation, through which experimentation and application of emerging new technologies are conducted. Moreover, R&D activities drive continuous product and service improvements, accelerate technological renewals, and shorten innovation cycles, enabling firms to adapt quickly to market changes and maintain a leading edge in digital transformation. Nelson and Winter (1982) and Furman, Porter, and Stern (2002) establish a theory supporting the link between R&D activities and innovation.

Second, Romer (1990), Hall and Lerner (2010), and Liu, Zhang, and Kuang (2023), among others, discuss that firms' marginal return on innovation improves through digital finance by reducing financial constraints and facilitating access to information, leading to higher R&D intensity. The innovation-driven growth theory emphasizes the pivotal role of R&D investment in enhancing both the vitality and efficiency of innovation. They cultivate a culture of exploration and experimentation, attract and retain innovative talent, and promote open communication and cross-functional collaboration, altogether creating a dynamic environment that nurtures digital innovation. Furthermore, R&D investment enhances production efficiency, enables the optimal allocation of both internal and external innovation resources, and accelerates the commercialization of digital innovation.

Third, the resource-based view positions R&D activities as a central mechanism for accumulating intangible assets such as patents, proprietary knowledge, and specialized technology teams. These resources confer legal protections, establish technical barriers, and provide enduring competitive advantages that underpin digital innovation, enabling firms to carve out unique strategic positions (see Barney, 1991). As Grant (1996) observes, R&D efforts also foster the development of specialized human capital, which is critical for driving digital innovation. Furthermore, firms develop and sustain repositories of knowledge embedded with technical expertise and best practices, forming a solid foundation for innovation and enhancing their ability to solve complex problems (see Zahra and George, 2002). From a dynamic capabilities perspective, R&D

facilitates the continuous reconfiguration and upgrading of internal resources in response to technological change, thereby strengthening a firm's long-term innovative capacity (see Teece, Pisano, and Shuen, 1997). Collectively, these perspectives suggest that R&D not only reflects a firm's absorptive capacity but also serves as a critical transmission channel through which external support programs stimulate innovation, as Cohen and Levinthal (1990) emphasize.

These various perspectives on R&D activities suggest that they not only reflect a firm's absorptive capacity but also function as a critical transmission channel through which external support programs foster innovation, as noted by Cohen and Levinthal (1990).

Although the existing literature suggests that Fintech programs can stimulate firm innovation by encouraging R&D activities, few studies have empirically tested whether Fintech programs indeed promote innovation. In this study, we explicitly construct an econometric model to examine the mediating role of R&D activities in the context of government-led Fintech pilot zones. To this end, we specify the following hypothesis:

$\mathscr{H}_2$: Fintech pilot programs promote digital innovation in part by increasing firms' R&D intensity.

2.3 Firm Heterogeneity: Absorptive Capacity and Digital Readiness

Firms with stronger absorptive capacities are more likely to transform Fintech support into meaningful digital innovation. According to the resource-based view, firms with well-developed internal capabilities, such as skilled human capital, robust IT infrastructure, and heightened digital awareness, are better positioned to capitalize on external changes (see, Barney, 1991; Cohen and Levinthal, 1990, for example). Recent evidence from China indicates that firms with higher digital competence not only attract more external financial support but also increase their R&D investment in response to Fintech reforms (see Tang, Chen, Chen, Quan, and Guan, 2023).

Firms differ in their response to the incentives provided by Fintech programs, largely depending on their internal capabilities. High-tech firms typically possess stronger dynamic capabilities, enabling them to swiftly adapt to environmental changes and reconfigure resources more effectively (e.g., Teece et al., 1997). They also tend to exhibit greater absorptive capacities, allowing them to better recognize, assimilate, and apply new technologies offered through digital finance platforms (see Cohen and Levinthal, 1990). Empirical evidence shows that such firms are more proactive in adopting digital tools in response to external disruptions and incentives, including Fintech initiatives, due to their solid technological foundations. In contrast, non-high-tech firms often lack the technical expertise or organizational flexibility required to fully benefit from these programs (see Bughin et al., 2017).

Nevertheless, existing studies have not systematically examined how firm heterogeneity operates within a causal framework, particularly concerning differences in digital readiness. To address this gap, we test the following hypothesis using empirical data from Chinese enterprises:

$\mathscr{H}_3$: Fintech pilot programs have a stronger effect on high-tech firms than non-high-tech firms.

2.4 Regional Heterogeneity: Financial Infrastructure and Inclusive Digitalisation

The impact of Fintech programs can vary across regions, depending on the strength of local financial infrastructure and the extent of digital service adoptions. In China, eastern regions generally possess more developed financial markets and advanced digital ecosystems. In contrast, central and western regions rely more hravily on the program-led financial expansion, as noted by Li, Feng, and Xie (2023). Furthermore, Lu, Wu, Li, and Nguyen (2021) find that Fintech programs yield greater improvements in credit access in areas where banking systems and services are less developed. These patterns suggest that the effectiveness of Fintech programs may differ by region, depending on the initial level of financial development. According to the institutional compensation effect, polict interventions tend to be more pronounced in regions where market institutions are relatively weak (see Rodrik, 2008).

Nevertheless, it remains unclear whether Fintech programs help reduce regional disparities in innovation or inadvertently reinforce existing gaps. Further causal analysis is required to assess the distributional effects of government-led digital finance initiatives across regions. To this end, we test the following hypothesis using empirical data from Chinese enterprises:

$\mathscr{H}_4$: Fintech pilot programs exert a stronger impact in central and western regions than in eastern regions.

3 Empirical Design

In this section, we describe the data employed for the empirical analysis and outline the empirical models specified to test the hypotheses presented in Section 2.

3.1 Data and Variables

Our dataset is compiled from three distinct sources. First, we utilize data from Chinese A-share listed companies—those traded in Renminbi on the Shanghai and Shenzhen stock exchanges—covering the period from 2009 to 2023, thereby forming a panel dataset. However, not all firms listed are included; the following types of companies are excluded from the sample:

(a) ST-, *ST-, and PT-indexed firms. These firms are subject to special treatment or may have been removed from the A-share list due to financial or operational distress;
(b) Firms that experienced status changes between the treatment and control groups during the sample period, with the definitions of these groups detailed below;
(c) Firms in financial industry;
(d) Firms with less than one period before implementing the Fintech program;
(e) Firms with missing observations;
(f) Firms with single-observation.

In addition to the exclusions mentioned above, continuous variables are winsorized at the 1st and 99th percentiles. Information on the financial technology pilot programs is sourced from the *Pilot Implementation Plan for Promoting the Integration of Science, Technology, and Finance*, published by the Ministry of Science and Technology of the People's Republic of China. Finally, corporate data are obtained from the Guotai'an database and the annual reports of listed companies.

We ensure that our sample aligns with the policy's target beneficiaries. For this, we verify that the composition of A-share listed firms reasonably represents the population of enterprises targeted by the Fintech Pilot Program. Although the policy documents emphasize "technology-based small and medium-sized enterprises (SMEs)," the program's design is not SME-exclusive. The instruments and institutions established under the pilot zones—such as risk-compensation funds, IP pledge credit, technology insurance, venture capital guidance funds, and regional technology–finance service platforms—also extend benefits to high-tech and strategically emerging industry firms, including A-share listed companies and their subsidiaries. According to market data as of the end of 2023 (Wind Information Co., Ltd. and Xueqiu Research Center (2023)), approximately 78% of A-share listed firms had a market capitalization below RMB 20 billion, and about 87% below RMB 50 billion. Furthermore, around 20% of A-share firms were listed on innovation-oriented boards such as ChiNext, STAR, or the Beijing Stock Exchange. Following the *Classification Standards for Small and Medium-sized Enterprises* issued by Ministry of Industry and Information Technology (MIIT) (2011), which define SMEs based on operating revenue, total assets, and employment thresholds (with revenue limits of RMB 400 million for medium-sized and RMB 200 million for small firms in the manufacturing sector), it is reasonable to consider that the majority of A-share firms fall within the SME range. Hence, the A-share dataset effectively represents the policy's intended beneficiaries while also capturing spillover effects on larger innovative enterprises.

Using the variables in the dataset, we classify them into four categories. The first category variable is the dependent variable of our econometric models. To this end, we define a variable representing the level of corporate digital innovation, denoted as *dinv*, which serves as the key variable of interest.

We define the dependent variable differently from those in the prior conventional metrics measuring digital innovation. Recent studies have increasingly examined the relationship between Fintech development and firm innovation, often focusing on market-driven Fintech services such as digital payments, online lending, and crowdfunding. These tools help alleviate credit constraints and improve capital allocation, particularly for small- and medium-sized enterprises. For instance, Ding et al. (2022) construct a Fintech index for 331 Chinese cities and find that stronger local Fintech activity correlates with higher patent counts and greater R&D intensity. Similarly, Ma and Li (2019) and Shen et al. (2022) demonstrate that Fintech pilot zones promote regional innovation and digital transformation by measuring digital innovation outcomes. International evidence also confirms that digital lending and crowdfunding channel funds toward innovation-intensive firms often underserved by traditional banks (e.g., Claessens, Frost, and Turner, 2018; Bollaert, Eicher, and Kung, 2021).

However, these studies typically rely on traditional innovation metrics such as patent counts or R&D expenditure, which primarily capture technological inventions but may overlook other forms of innovation, including digital upgrades, business model innovations, or service transformations. Consequently, focusing solely on conventional metrics risks neglecting firms' broader strategic responses to digital finance. For example, the UK Financial Conduct Authority's regulatory sandbox reduced compliance costs and encouraged experimentation, fostering innovation (e.g., Lu, 2018). Likewise, government-supported supply-chain finance platforms in China enhance firms' credit access and credibility (e.g., Song, Han, Liu, and Ganguly, 2023). Such innovations are challenging to capture with traditional indicators.

A smaller but growing body of research adopts alternative metrics to assess government-led Fintech initiatives. Fintech pilot programs are designed to foster supportive environments for financial innovation, yet few studies offer clear insights into how firms adjust their internal strategies in response to these programs. In line with Zheng and Zhuang (2024), we adopt a measure of digital innovation developed in the context of judicial specialization in intellectual property rights. Specifically, we construct a text-based indicator derived from firms' annual reports. This method identifies 99 keywords associated with digital product, digital process, and digital business model innovations. We then calculate the frequency of these keywords and normalize it by the total word count of each report. This approach enables us to capture a broader and more dynamic picture of digital innovation than traditional patent-based proxies. It is constructed through the following three-step procedure:

Step 1: We select seed words from two official documents: the *Special Action Plan for Digital Empowerment of Small and Medium Enterprises* and the *2020 Digital Transformation Trends Report*;

Step 2: Next, we expand the initial set of seed words using a machine learning approach, ultimately constructing a digital innovation lexicon comprising 99 keywords across three dimensions: digital product, digital process, and digital business model innovations;

Step 3: Finally, we extract the frequency of digital innovation terms from the annual reports and calculate their proportion relative to the total text length of each report. The resulting proportions are generally small. To eliminate scale-related effects, we multiply these proportions by 1,000 and define the final value as *dinv*. This variable serves as our dependent variable, representing the level of digital innovation among Chinese firms between 2009 and 2023.

The text-based digital innovation index is established by its own theoretical ground. The 99 keywords employed in this study were categorized into three groups—digital product, digital process, and digital business model innovation—following the taxonomy proposed in the OECD/Eurostat (2018). This framework ensures that the indicator captures multiple dimensions of firms' digital transformation, including technological upgrading, operational digitalization, and strategic reconfiguration. Furthermore, the text-based measurement approach has been recognized in recent literature as a valid proxy for real innovation activities. For example, Zheng and Zhuang (2024) construct a similar keyword-based index to measure firms' digital innovation in the context of judicial specialization in intellectual property, confirming its robustness in reflecting innovation intensity. Doh, Magni, Sifonis, and Brush (2022) also find that text-based indicators of "digital orientation," "digital maturity," and "digital intensity" are strongly correlated with firms' innovation investment, productivity, and financial performance. These studies demonstrate that keyword frequency extracted from corporate reports can serve as a reliable and theoretically grounded indicator of firms' digital innovation. Based upon this, our text-based digital innovation index captures not only linguistic emphasis in corporate reports but also firms' substantive engagement in digital technology adoption, process optimization, and business model transformation.

The second category is the explanatory variable used to implement the DID approach. To this end, we define treatment and control groups based on the Fintech pilot programs. Following Ma and Li (2019) and Shen et al. (2022), we define the program variable at the city level, corresponding to the city in which each company is listed. Specifically, Fintech pilot programs were launched in 41 cities in 2011,[2] with additional 9 cities included in 2016.[3]

Using this information, we define two binary variables: *treat* and *post*. A company is assigned a value of 1 for *treat* if it is located in a pilot program city, and 0 otherwise. This definition follows the official designation of Fintech Pilot Zones by the People's Bank of China (PBoC) and local financial authorities, where

[2]These include Beijing, Tianjin, Shanghai, Nanjing, Wuxi, Xuzhou, Changzhou, Suzhou, Nantong, Lianyungang, Huai'an, Yangzhou, Zhenjiang, Taizhou, Suqian, Hangzhou, Wenzhou, Huzhou, Hefei, Bengbu, Wuhu, Wuhan, Changsha, Guangzhou, Foshan, Dongguan, Chongqing, Chengdu, Mianyang, Xi'an, Baoji, Tianshui, Weinan, Tongchuan, Shangluo, Qingyang, Pingliang, Longnan, Dalian, Qingdao, and Shenzhen.

[3]These cities are Zhengzhou, Xiamen, Ningbo, Jinan, Nanchang, Guiyang, Yinchuan, Baotou, and Shenyang.

eligibility is determined by the *registered location* of firms. According to the implementation guidelines, only entities registered as independent legal persons within the pilot zones are entitled to directly enjoy the policy benefits or regulatory facilitation, whereas branch offices or representative units are not. For example, the Guangdong Provincial People's Government Office (2016) explicitly require that "the applicant must be a company located in the Guangzhou area," illustrating that Chinese innovation and financial-support programs operate based on firms' registered location rather than their operational coverage. Therefore, our identification strategy—classifying firms as treated if their headquarters are registered in pilot cities—is both institutionally consistent and empirically precise. The variable *post* equals 1 if the year of the observation is the same as or later than the year the program was implemented in the corresponding treatment city, and 0 otherwise. Based on these two variables, we define *did* as their interaction term: *did* = *treat* × *post*. Although *did* is a simple binary indicator distinguishing firms exposed to the program from those that are not, it serves as the key variable for identifying the causal effect of Fintech pilot programs by the DID methodology.

The third category includes control variables used to improve the precision of the causal estimates. In addition to the dependent variable (*dinv*) and the explanatory variable (*did*), we incorporate a set of firm-level control variables. Following Shen et al. (2022) and Ma and Li (2019), these controls include the following:

(a) Firm size (*size*) is included as larger firms typically possess more resources and greater capacity to support innovative activities. We define *size* as the natural logarithm of (1 + total assets).

(b) Leverage ratio (*lev*) is included, as firms with higher leverage may limit their investment in innovation due to financial pressure and risk aversion. We define *lev* as the ratio of total liabilities divided by total assets.

(c) Return on equity (*roe*) is included because firms with higher *roe* typically have stronger internal financing capacities for R&D activities. We define *roe* as the net income divided by shareholders' equity.

(d) Inventory ratio (*inv*) is included because a high level of inventory may tie up capital and reduce the firm's ability to invest in R&D activities. We define *inv* as inventory divided by total assets.

(e) Fixed asset ratio (*fixed*) is included because capital-intensive firms may face higher costs and lower flexibility in implementing innovations. We define *fixed* as fixed assets divided by total assets.

(f) Accounts receivable ratio (*rec*) reveals firm's liquidity status. A high *rec* can constrain cash flow, limiting funds available for innovation. We define *rec* as accounts receivable divided by total assets.

(g) Board size (*board*) may bring diverse expertise from its members, but can also slow down decision-making processes related to innovation. We define *board* as the natural logarithm of (1 plus the number of board members).

(h) Ownership concentration (*top10*) is included because highly concentrated ownership may promote short-term decision-making, whereas more dispersed ownership can encourage long-term innovation. We define *top10* be the shareholding ratio held by the top 10 shareholders.

(h) Management shareholding (*mshare*) is included because management ownership helps align incentives and supports long-term innovation goals. We define *mshare* as the proportion of shares held by executive members relative to total shares.

The final category variable is included to explore the underlying mechanism through which the program influences digital innovation. To this end, we incorporate R&D intensity (*rdinc*) as a mediating variable. Following Li, Peng, and Tan (2021), *rdinc* is defined as the ratio of current R&D expenditure to lagged operating revenue. This variable captures the firm's investment in technological development relative to its revenue scale. By including *rdinc*, we aim to test whether Fintech pilot programs promote digital innovation through R&D activities.

All dependent, explanatory, control, and mediating variables are summarized in Table 1.

3.2 Empirical Models

To achieve the objectives of this study, we present the econometric models used for the empirical analysis.

First, we specify the following model as our baseline model:

$$\begin{aligned} dinv_{i,t} =& \alpha_0 + \alpha_1 did_{i,t} + \alpha_2 size_{i,t} + \alpha_3 lev_{i,t} + \alpha_4 roe_{i,t} + \alpha_5 fixed_{i,t} + \alpha_6 rec_{i,t} \\ & + \alpha_7 inv_{i,t} + \alpha_8 board_{i,t} + \alpha_9 top10_{i,t} + \alpha_{10} mshare_{i,t} + \lambda_i + year_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where i and t denote the indeices for individual firms and years, respectively. α_0 is the intercept, α_1 to α_{10} are the coefficients of the explanatory and control variables, λ_i represents the firm-fixed effect, $year_t$ denotes the year-fixed effect, and $\varepsilon_{i,t}$ is the idiosyncratic error term.

We aim to identify the causal impact of Fintech pilot programs on digital innovation using model (1) within a DID framework. The core idea is to compare changes in digital innovation between firms located in pilot cities (treatment group) and those in non-pilot cities (control group) before and after the implementation of the programs. The coefficient α_1 captures the average difference in innovation growth between the treatment and control groups following the program launch. A positive and statistically significant α_1 would indicate that the programs have a favorable effect on digital innovation. Here, to control for unobserved, time-invariant firm characteristics, we include firm fixed effects (λ_i). Year fixed effects ($year_t$) are also added to account for macroeconomic shocks or common time trends that may influence all firms simultaneously. Together, these controls help mitigate omitted variable bias and enhance the credibility of our causal estimates.

Second, we examine the mediating role of R&D intensity by investigating how it is influenced by Fintech pilot programs and, in turn, how it contributes to digital innovation. This analysis follows the three-step mediation approach proposed by Wen and Ye (2014). As the first step, we use model (1) to estimate the total effect of the Fintech pilot programs on digital innovation. In the second step, we estimate the following model to assess the impact of the programs on the mediating variable:

$$\begin{aligned} rdinc_{i,t} =& \alpha_0 + \alpha_1 did_{i,t} + \alpha_2 size_{i,t} + \alpha_3 lev_{i,t} + \alpha_4 roe_{i,t} + \alpha_5 fixed_{i,t} + \alpha_6 rec_{i,t} \\ &+ \alpha_7 inv_{i,t} + \alpha_8 board_{i,t} + \alpha_9 top10_{i,t} + \alpha_{10} mshare_{i,t} + \lambda_i + year_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

As in model (1), we apply the DID framework to specify model (2). This model investigates whether Fintech pilot programs have an impact on firms' R&D activities, measured by R&D *rdinc*. Both firm fixed effects and year fixed effects are included to account for unobserved heterogeneity and time-specific shocks. The objective is to evaluate whether the programs affect the proposed mediating variable. A positive and statistically significant coefficient on *did* would indicate that the Fintech pilot programs influence R&D activities. Conversely, if the coefficient is not statistically significant, the existence of a mediation pathway is unlikely.

Finally, we specify the third-step model as follows:

$$\begin{aligned} dinv_{i,t} =& \alpha_0 + \alpha_1 did_{i,t} + \alpha_2 rdinc_{i,t} + \alpha_3 size_{i,t} + \alpha_4 lev_{i,t} + \alpha_5 roe_{i,t} + \alpha_6 fixed_{i,t} + \alpha_7 rec_{i,t} \\ &+ \alpha_8 inv_{i,t} + \alpha_9 board_{i,t} + \alpha_{10} top10_{i,t} + \alpha_{11} mshare_{i,t} + \lambda_i + year_t + \varepsilon_{i,t} \end{aligned} \tag{3}$$

As in the previous models, we employ the DID framework to estimate model (3). Here, the mediating variable *rdinc* is included on the right-hand side to assess its role in transmitting the effect of the Fintech pilot programs on digital innovation. A statistically significant *rdinc* coefficient, along with a reduced magnitude of the *did* coefficient compared to model (1), would provide evidence supporting the existence of a mediation pathway.

The estimation of this model allows us to assess whether Fintech pilot programs promote digital innovation fully or partially through R&D activities. If the coefficient on *rdinc* in model (3) is positive and statistically significant, while the coefficient on did becomes statistically insignificant, this suggests that the effect of the Fintech programs on digital innovation is fully mediated by R&D activities. Conversely, if both *did* and *rdinc* are positive and statistically significant, it indicates a partial mediation effect—meaning that R&D activities account for part, but not all, of the programs' impact on digital innovation.

4 Empirical Outputs

In this section, we conduct the empirical analysis using the data and econometric models outlined in Section 3, and present the estimation results along with their implications.

Before presenting the empirical results, we first provide descriptive statistics, summarized in Table 2. Several features are noteworthy. First, the sample average of *dinv* is 7.1178, with a minimum of 0 and a maximum of 52.291. This indicates that while some listed firms have not engaged in digital innovation, others demonstrate relatively high levels of digital innovation activity. Second, the sample average of *did* is 0.4705, suggesting that approximately 47.0% of the listed firms were exposed to the Fintech pilot programs. Finally, the sample average of *rdinc* is 0.0502, ranging from 0 to 0.3019. This implies that some firms did not undertake any R&D activity, whereas others invested up to 30.2% of their lagged operating revenue in R&D.

4.1 Baseline Model Regression

We now turn to the discussion of the baseline model estimation results. Based on model (1), the results are presented in Table 3.

We summarize the estimation results as follows. Column (1) of Table 3 presents the fixed effects regression without control variables, showing that *did* has a significantly positive effect on dinv. Column (2) reports the results with control variables included, and the coefficient on *did* remains positive and statistically significant. Specifically, the coefficient is estimated at 0.8225, indicating that the Fintech integration programs have led to a measurable increase in the level of digital innovation. This suggests that the programs have been effective in promoting digital innovation among the listed firms.

We further interpret the magnitude of this coefficient. For this, we assess its economic significance relative to the sample mean. Given that the average digital innovation index (*dinv*) is approximately 4.3 per thousand words, the estimated coefficient of 0.8225 implies an increase of about 19 percent relative to the mean level of digital innovation among A-share firms. In other words, after the implementation of the Fintech Pilot Program, firms' textual emphasis on digital transformation, artificial intelligence, and smart manufacturing increased substantially, reflecting a genuine shift in strategic priorities toward digital upgrading and technological investment. This magnitude is comparable to those documented in previous studies such as Ding et al. (2022) and Howell (2016), confirming that the estimated effect is both statistically and economically meaningful. Moreover, this finding aligns with the mediation analysis presented later in the paper, which shows that the Fintech Pilot Program promotes digital innovation partly by enhancing firms' R&D intensity. Hence, the baseline estimation provides not only causal evidence of policy impact but also economically significant implications for firms' digital transformation.

Beyond the main explanatory variable, the control variables in column (2) of Table 3 provide additional insights into the determinants of dinv. First, *size* is positively and significantly associated with *dinv*, suggesting that larger firms are more likely to engage in digital innovation, likely due to their greater resources and capacity to support innovation activities. Second, *lev* has a significantly negative coefficient, indicating that firms under greater financial pressure tend to reduce investment in riskier activities such as R&D. Third, the coefficient on *fixed* is also negative and statistically significant, implying that capital-intensive firms may face structural rigidities that limit their adaptability to digital transformation. Fourth, both *inv* and *rec* are positively associated with *dinv*, suggesting that firms with higher levels of inventory and receivables may rely more heavily on digital tools to manage operations, optimize logistics, or monitor cash flows. Fifth, *board* shows a positive effect, indicating that larger boards may contribute diverse expertise and governance oversight, which could foster innovation. Sixth, *top10* is negatively and significantly associated with *dinv*, implying that highly concentrated ownership structures may emphasize short-term returns at the expense of long-term innovation strategies. Lastly, *mshare* exhibits a negative relationship with *dinv*, though the effect is only weakly significant.

Taken together, these results highlight that firm-level characteristics influence innovation behavior in theoretically consistent ways. Including these controls enhances the precision and credibility of our DID estimates.

To validate our estimation results, we conduct four additional tests: the parallel trends test, placebo test, propensity score matching test, and robustness test. We discuss the results of each test in turn.

Parallel Trend Test The validity of the DID estimation relies on the assumption that the treatment and control groups exhibit parallel trends in the outcome variable before the implementation of the Fintech pilot programs. To assess this, we examine whether changes in the dependent variable follow similar trajectories for both groups before the program's introduction. Following Hu, Yu, and Han (2023), we specify a dynamic DID model for the parallel trends test:

$$\begin{aligned} did_{it} = \alpha_0 &+ \sum_{s=-7}^{-1} \beta_s^{\text{pre}} \left[treat_i \times \mathbb{I}(t - T_D = s) \right] \\ &+ \sum_{s=0}^{13} \beta_s^{\text{las}} \left[treat_i \times \mathbb{I}(t - T_D = s) \right] + \lambda_i + \text{Year}_t + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where β_s^{pre} and β_s^{las} denote the coefficients of the pre- and post-program period dummy variables, respectively. The variable *treat* indicates whether a firm belongs to the treatment group or not, and $\mathbb{I}(\cdot)$ is the indicator function. T_D represents the year the program was implemented. We set $s = -1$ as the reference year by following Liu and Yu (2022) and Li, Wang, and Zhang (2022).

We estimate the unknown coefficients by regressing the dependent variable on the right-hand side variables. If there exists no difference in trends between the two groups before the program implementation, the coefficients of β_s^{pre} should be zero for all $s < 0$. Conversely, if the treatment group is affected by the programs, the coefficients of β_s^{las} are expected to be positive for all $s > 0$.

The results of the parallel trends test are summarized in Figure 1, which displays the confidence intervals of the estimated coefficients. First, during the pre-treatment periods from -7 to -2, the confidence intervals of the coefficients are centered around zero, and the estimates are not statistically significant. This indicates no significant difference in digital innovation trends between the treatment and control groups before program implementation. Second, in the post-treatment periods from 2 to 12, the estimated coefficients exhibit a marked increase. Their confidence intervals do not overlap with zero and lie entirely in the positive region, signaling a significant divergence in digital innovation between the treatment and control groups following the program's introduction. The treatment group shows a notably higher level of digital innovation compared to the control group, providing strong evidence that the Fintech pilot programs have effectively promoted digital innovation among the listed enterprises.

Placebo Test We further conduct a placebo test to verify that the observed effects on digital innovation are genuinely attributable to the Fintech pilot programs, rather than random external shocks or influences from other confounding factors. Following the approach of Ferrara, Chong, and Duryea (2012), we perform a 500-sample randomization procedure to generate pseudo-program dummy variables. We then estimate the baseline model for each sample and calculate the corresponding p-values from the t-tests. By comparing the estimation results from the actual data with those obtained from the randomized samples, we assess whether the observed program effects differ significantly from what would be expected by chance. If the programs are truly effective, the estimated coefficient from the real data should stand out distinctly from the distribution of coefficients generated by the randomization.

The test results are summarized in Figure 2. First, the estimated coefficients from the 500 random samples are approximately normally distributed around zero, with most estimates statistically insignificant and the majority of p-values exceeding 0.1. In contrast, the regression coefficient from the actual data is 0.8225, which lies well outside the approximate range of the placebo estimates [-0.4,0.4]. This provides strong evidence that the observed effect of the Fintech pilot programs on digital innovation is genuinely attributable to the programs themselves, rather than to random external shocks or concurrent interventions.

Propensity Score Matching We employ propensity score matching (PSM) to re-match the treatment and control samples and conduct further regression analysis. PSM is used to address concerns that the treatment and control groups were originally selected from all companies listed on the A-share market without filtering. As a result, significant differences between the two groups may exist, potentially leading to sample self-selection bias and other endogeneity issues. These issues could distort the regression results reported in Table 3.

We estimate the propensity scores. For this, we follow the approach of Alfaro-Urena, Manelici, and Vasquez (2022) and include a comprehensive set of firm-level covariates that may jointly affect both the likelihood of being located in a Fintech Pilot Zone and the firm's digital innovation capacity. Specifically, the logit estimation incorporates firm size (*Size*), leverage (*Lev*), profitability (*ROE*), investment (*INV*), asset tangibility (*FIXED*), receivables (*REC*), board characteristics (*Board*), ownership concentration (*Top10*), and managerial shareholding (*Mshare*). These covariates capture firms' financing capacity, operational structure, and corporate governance characteristics, ensuring that treatment assignment is based on comparable firm fundamentals.

For the PSM procedure, we employ the nearest-neighbor matching method and implement three matching strategies: hybrid matching, year-by-year matching, and individual (one-to-one) matching. The hybrid matching method performs PSM across the entire sample, while the year-by-year matching conducts PSM separately for each year. For individual matching, the treatment group samples are divided based on the program entry years—2011 and 2016—and each subgroup is matched with the full set of control group samples. After applying these three PSM strategies, we construct wide-panel datasets so that matched pairs are formed at the firm-to-firm level. Notably, the individual matching method effectively addresses data discontinuity issues in the control group that may arise with the hybrid and year-by-year matching methods.

We verify the quality of matching. For this, we report the covariate balance statistics before and after matching in Table 4 and provide graphical evidence of standardized mean differences in Figure 3 (Hybrid Matching) and Figure 4 (Year-by-Year Matching). The results show that the *Mean Bias* decreases from approximately 11.8% before matching to 1.6–1.7% after matching, while the *Med Bias* decreases from 4.6% to about 1.3–1.5%. These findings confirm that the covariate balance between the treatment and control groups has been substantially improved after matching.

Table 5 shows that the DID approach continues to yield a significant positive effect on *dinv*. Across all three PSM methods, the estimated coefficients for *did* remain positive and statistically significant. This confirms that the integration of financial technology through the program effectively promotes digital innovation, reinforcing the findings from the baseline model estimation.

Robustness Test To ensure the robustness of the baseline model estimation, we employ three methods as follows: (1) we account for heterogeneity across industries by including industry-fixed effects as additional control variables, aiming to eliminate the influence of industry-specific factors; (2) we address program impacts at the provincial and industry levels by incorporating province-year and industry-year interaction fixed effects, which capture program shocks affecting firm digital innovation across different regions and sectors over time.

The results are reported in Table 6. Even after including industry-fixed effects, province-year interaction fixed effects, and industry-year interaction fixed effects, the regression results consistently show a significantly positive impact of *did* on *dinv*. This further confirms the robustness of the baseline model estimation.

4.2 Mediation Analysis

In this section, we conduct regression analysis based on the mediation effect framework by further estimating models (2) and (3). The corresponding results are presented in Table 7.

The estimation results are summarized as follows. First, column (1) presents the effect of *did* on *rdinc*. The coefficient of *did* is 0.0024 and statistically significant at the 5% level, indicating that the Fintech programs effectively promote R&D investment among firms in the treatment group. Second, column (2) reports the effects of both *did* and *rdinc* on *dinv*. The results show that both coefficients are positive and statistically significant. According to the three-step mediation testing procedure, this implies that Fintech programs enhance digital innovation partially through the channel of increased R&D investment.

4.3 Heterogeneity Analysis

In this section, we account for the fact that individual firms operate in heterogeneous environments. We investigate how the previous regression results are affected by three sources of heterogeneity: technological differences, regional differences, and their combined (composite) effect.

Heterogeneity by high-tech vs. Non-high-tech Firms Firms exhibit varying levels of technological capability, which may shape the way they implement digital innovation. To account for this heterogeneity, we classify firms into high-tech and non-high-tech groups and conduct separate regression analyses for each. A firm is designated as high-tech if its primary industry code falls within the high-technology sectors defined by the *Guidelines for the Classification of Listed Companies' Industries* (2012 Revision), the *Strategic Emerging Industry Classification Catalogue* (2012, pilot version), and relevant OECD standards. Following Peng and Mao (2017), we identify high-tech firms as those with industry codes in the following ranges: C25–C29, C31–C41, I63–I65, and M73. Firms whose industry codes fall outside these categories are classified as non-high-tech.

The estimation results are presented in Table 8. The coefficient of *did* remains positive and statistically significant for high-tech firms, while it is statistically insignificant for non-high-tech firms. This suggests that the impact of Fintech pilot programs on digital innovation is more pronounced among high-tech enterprises.

The estimation results suggest that Fintech programs are more aligned with the interests of high-tech firms than those of non-high-tech companies. High-tech firms benefit more from these programs for several reasons. First, being more technologically sensitive and responsive to innovation-driven initiatives, high-tech firms tend to operate at the technological frontier, with greater awareness of and capacity to adopt emerging technologies. Fintech programs not only provide financial support but also offer access to cutting-edge technological information, market intelligence, and regulatory guidance—resources that are especially critical for driving digital innovation in high-tech sectors. Consequently, high-tech firms are better positioned to leverage these programs and convert them into tangible innovation outcomes. In addition, their strong technological foundations enable them to adapt and optimize technical solutions more flexibly in response to program changes and evolving market demands.

Second, high-tech firms typically have stronger incentives for innovation and more mature innovation systems. They often operate in highly competitive markets that require continuous technological advancement and product innovation. These internal motivations drive high-tech firms to proactively pursue and implement digital innovation. In this context, Fintech programs offer incentives that support the establishment of dedicated R&D departments, mechanisms for interdisciplinary collaboration, and corporate cultures that promote experimentation and creativity—all of which align closely with the strategic interests of high-tech firms.

Third, high-tech firms demonstrate a stronger propensity to allocate resources toward R&D activities and digital transformation, viewing such investments as strategic drivers of long-term growth and competitiveness. Fintech programs provide additional support—such as fiscal subsidies, tax incentives, and preferential loan access—that significantly reduce the costs and risks associated with innovation. As a result, high-tech firms effectively channel these resources into strategically important areas, including core technology R&D, digital infrastructure development, and talent acquisition. Through these efforts, high-tech firms achieve greater resource efficiency and accelerate the speed and quality of their digital innovation compared to non-high-tech firms.

Heterogeneity Analysis Across Regions Firm location is also a relevant factor in digital innovation, as heterogeneous regional environments can lead to varying effects. In China, enterprises face distinct business conditions between the eastern and central-western regions. To capture this heterogeneity, we classify the listed firms into two groups—those located in the eastern region and those in the central and western regions—and conduct separate regression analyses for each group.[4]

The estimation results are presented in Table 9. The coefficients of *did* are positive and statistically significant for both regions. For firms in the eastern region, the effect is significant at the 10% level, with a coefficient of 0.4984. In contrast, for firms in the central and western regions, the effect is significant at the 1% level, with a larger coefficient of 1.2419. These results indicate that the impact of *did* on digital innovation is more pronounced in the central and western regions than in the eastern region.

To further examine the regional disparity, we test the difference between the coefficients for the eastern and central-western regions using Fisher's Z-test. The results are reported in Table 10. The p-value for the difference in the estimated did coefficients is 0.07, indicating statistical significance at the 10% level. This finding reinforces the conclusion that the impact of Fintech pilot programs on digital innovation is more pronounced in the central and western regions than in the eastern region.

The estimation results suggest several implications. First, firms in the eastern region operate in a highly competitive environment, characterized by a dense concentration of enterprises and capital, as well as more mature market mechanisms. This environment compels firms to continuously strengthen their internal innovation capabilities to maintain competitiveness. Consequently, the marginal impact of Fintech programs is likely to be limited, as many of these firms are already embedded in fast-evolving, innovation-driven ecosystems. Moreover, eastern firms often follow established innovation trajectories, which may dilute the incremental benefits of Fintech pilot programs.

Second, the eastern region benefits from well-organized industrial chains and ecosystems, which provide firms with abundant innovation resources and diverse channels for collaboration. These include both vertical and horizontal integrations with upstream and downstream partners, participation in industrial alliances, and strong partnerships among industry, academia, and research institutions. As a result, firms in the eastern region tend to possess greater independence and internal capabilities for innovation, reducing their reliance on external support.

In contrast, the industrial bases in the central and western regions are relatively less developed. Firms in these areas often face greater barriers to accessing the resources necessary for innovation. In this context, external support—particularly through Fintech pilot programs—plays a critical role in fostering digital innovation. These programs not only provide financial assistance but also help firms access advanced tech-

[4]Following Shen, Chen, and Lin (2021), firms are categorized into three groups based on their registered provinces. The eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes Shanxi, Jilin, Heilongjiang, Henan, Hubei, Hunan, Anhui, and Jiangxi. The western region includes Inner Mongolia, Chongqing, Sichuan, Guangxi, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, and Tibet.

nologies, expand market reach, and develop human capital. For firms in the central and western regions, such comprehensive support can effectively compensate for weaker local ecosystems, thereby facilitating digital transformation and enhancing innovation outcomes.

Heterogeneity by high-tech vs. Non-high-tech firms across region We further conduct a regression analysis that accounts for the combined heterogeneity stemming from both firms' technological levels and regional differences. To this end, we classify the firms into four categories: (1) high-tech firms in the eastern region, (2) high-tech firms in the central and western regions, (3) non-high-tech firms in the eastern region, and (4) non-high-tech firms in the central and western regions. For each group, we estimate the baseline model separately and discuss the implications of the results.

The estimation results are presented in Table 11. We find that the Fintech pilot programs have a significantly positive effect on digital innovation only for high-tech firms located in the central and western regions. For this group, the estimated coefficient of *did* is 1.8736 and is statistically significant at the 1% level. In contrast, the estimated coefficients for the other three groups are not statistically significant, indicating that the impact of the programs is not evident among high-tech firms in the eastern region or among non-high-tech firms regardless of region.

This finding indicates that Fintech pilot programs are most effective for firms that combine strong internal innovation capabilities with external environments characterized by less developed digital infrastructure and financing channels. High-tech firms in the central and western regions benefit the most, as they possess the absorptive capacities necessary to leverage the financial and technological resources offered by the programs. Moreover, these firms operate in regions where pre-existing support mechanisms are relatively limited, making the impact of the programs more pronounced. In contrast, high-tech firms in the eastern region experience only marginal benefits from the programs, as they are already embedded in well-established innovation ecosystems. For non-high-tech firms in both regions, weaker innovation capacities hinder their ability to effectively utilize the policy incentives provided by the programs.

Overall, this analysis of composite heterogeneity underscores that the effectiveness of policy interventions depends not only on firms' internal capabilities but also on the external environments in which they operate. Fintech pilot programs can serve as powerful catalysts for innovation, especially when directed toward technologically capable firms in regions with underdeveloped digital infrastructure.

5 Conclusion

This study evaluates the impact of China's Fintech pilot programs on firm-level digital innovation. Leveraging a quasi-natural experiment and a multi-period DID framework, we find that firms located in pilot zones exhibit significantly higher levels of digital innovation. Digital innovation is measured using the frequency of digital-related keywords in firms' annual reports, capturing their strategic engagement with digital technologies.

Our mechanism analysis reveals that part of this effect operates through increased R&D activities. By encouraging firms to invest more in technological capabilities, the programs enhance their innovation capacity. We also find that the program's impact is stronger for high-tech firms and for those located in the central and western regions. These findings suggest that Fintech pilot programs can help reduce regional disparities in innovation outcomes. Overall, well-designed Fintech initiatives, combined with targeted R&D support and infrastructure investment, can serve as powerful tools to promote inclusive digital innovation in emerging economies.

Despite strong evidence of the vital role of Fintech pilot programs, this study has several primary limitations. First, the sample is limited to A-share listed firms, which may not fully represent the behavior of smaller or unlisted enterprises. Second, although our text-based innovation measure provides broader coverage of digital innovation than conventional patent-based metrics, it may still fail to capture informal or internal innovation efforts comprehensively. Finally, although the treatment definition in this study strictly follows the official principle of eligibility based on registered location, some non-headquarter subsidiaries or affiliated firms outside the pilot cities may indirectly benefit from the Fintech Pilot Program through supply-chain linkages, financial cooperation, or up- and downstream relationships. If such positive spillovers exist, our estimated DID coefficients are likely to be conservative. In addition, we note that future research could further decompose the text-based digital innovation index to examine which specific keywords drive the observed effects, thereby offering deeper insights into the underlying mechanisms.

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Variable Type	Variable Name	Symbol	Definition
Dependent Variable	Digital Innovation	*dinv*	Frequency of digital innovation keywords in annual reports divided by the total text length of annual reports, multiplied by 100
Independent Variable	Program Effect	*did*	Equals 1 if the firm is located in a pilot city after the Fintech program is implemented; 0 otherwise
Mediating Variable	R&D Intensity	*rdinc*	R&D expenditure divided by lagged operating revenue
Control Variables	firm size	*size*	Natural logarithm of total assets plus 1
	leverage ratio	*lev*	Total liabilities divided by total assets
	return on equity	*roe*	Net income divided by shareholders' equity
	inventory ratio	*inv*	Inventory divided by total assets
	fixed asset ratio	*fixed*	Fixed assets divided by total assets
	accounts receivable ratio	*rec*	Accounts receivable divided by total assets
	board size	*board*	Number of board members plus 1, log-transformed
	ownership concentration	*top10*	Shareholding ratio of the top 10 shareholders
	management shareholding ratio	*mshare*	Number of shares held by executives divided by total shares

Table 1: VARIABLE DEFINITIONS. This table provides variable types, variable names, symbols and definitions for all variables used in the empirical analysis.

Variable	Obs.	Mean	SD	Min.	Max.
dinv	26746	7.1178	9.1855	0.0000	52.291
did	26746	0.4705	0.4991	0.0000	1.0000
rdinc	26746	0.0502	0.0520	0.0002	0.3019
size	26746	22.294	1.2944	19.983	26.275
lev	26746	0.4202	0.1992	0.0555	0.8827
roe	26746	0.0423	0.1579	-0.9415	0.3022
inv	26746	0.1331	0.1006	0.0006	0.5286
fixed	26746	0.2152	0.1449	0.0058	0.6543
rec	26746	0.1285	0.0977	0.0018	0.4505
board	26746	2.2366	0.1716	1.7918	2.7081
top10	26746	0.5639	0.1521	0.2213	0.8892
mshare	26746	0.0681	0.1311	0.0000	0.5797

Table 2: DESCRIPTIVE STATISTICS. This table reports the summary statistics of all key variables, including means, standard deviations, and ranges.

	(1)	(2)
Independent \ Dependent	*dinv*	*dinv*
did	0.7965***	0.8225***
	(0.2162)	(0.2119)
size		1.4289***
		(0.0893)
lev		-1.1531***
		(0.3234)
roe		0.0151
		(0.2395)
inv		1.0534*
		(0.6049)
fixed		-1.2790***
		(0.4046)
rec		5.1986***
		(0.7803)
board		1.1814***
		(0.2971)
top10		-2.4354***
		(0.4332)
mshare		-0.9465*
		(0.5145)
constant	6.7431***	-26.378***
	(0.1047)	(2.0084)
Individual FE	Yes	Yes
Time FE	Yes	Yes
Sample size	26746	26746
F-test	13.568***	38.343***
R^2	0.8294	0.8337

Table 3: BASELINE REGRESSION RESULTS. Figures in parentheses are the robust standard errors. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$. This table shows that the Fintech pilot programs significantly increases the level of corporate digital innovation. The coefficients are estimated by controlling for firm and time fixed effects.

Sample	R^2	LR	$p > \chi^2$	*Mean Bias*	*Med Bias*	B	R	$\%Var$
Unmatched	0.053	1970.90	0.000	11.8	4.6	55.4*	1.00	78
Matched (Mixed Matching)	0.001	22.38	0.008	1.6	1.5	5.7	0.97	78
Matched (Year-by-Year Matching)	0.001	29.49	0.001	1.7	1.3	6.6	1.04	67

Table 4: COVARIATE BALANCE BEFORE AND AFTER PROPENSITY SCORE MATCHING. This table reports the overall balance statistics from the propensity score matching (PSM) procedure. "Unmatched" refers to the full sample before matching, while "Matched" reports the results after matching under two specifications: mixed (pooled) matching and year-by-year matching. R^2 denotes the pseudo R-squared from the propensity score model; *Mean Bias* and *Med Bias* are the average and median standardized percentage bias across covariates; B measures the overall bias, and R denotes the ratio of treated to control variances. A value of B greater than 25% or R outside [0.5, 2] indicates potential imbalance.

	(1) Hybrid Matching	(2) Year-by-Year Matching
Independent \ Dependent	*dinv*	*dinv*
did	0.8501***	0.9212***
	(0.2139)	(0.2342)
size	1.3466***	1.2778***
	(0.0889)	(0.0925)
lev	-0.9555***	-1.2382***
	(0.3217)	(0.3208)
roe	0.0091	0.1090
	(0.2439)	(0.2403)
inv	0.8777	0.6599
	(0.6233)	(0.6233)
fixed	-1.3798***	-1.7179***
	(0.4050)	(0.4345)
rec	4.4534***	4.9553***
	(0.8069)	(0.7737)
board	1.1122***	0.9885***
	(0.3006)	(0.2848)
top10	-2.2095***	-1.3455***
	(0.4297)	(0.4389)
mshare	-0.9816*	0.4168
	(0.5173)	(0.4982)
constant	-24.522***	-23.316***
	(1.9987)	(2.0958)
Individual FE	Yes	Yes
Time FE	Yes	Yes
Sample size	26,239	24,163
F-test	34.176***	29.944***
R^2	0.8331	0.8487

Table 5: PSM-DID REGRESSION RESULTS. Figures in parentheses are robust standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the difference-in-differences (DID) estimates based on the matched samples obtained from two propensity score matching strategies—hybrid matching and year-by-year matching. Both approaches yield consistent and statistically significant results, confirming the robustness of the baseline findings.

	(1) Industry Fixed Effects	(2) Province Program Capture	(3) Industry Program Capture
Independent \ Dependent	*dinv*	*dinv*	*dinv*
did	0.8584***	1.0794***	0.4071**
	(0.2089)	(0.2560)	(0.2001)
size	1.3511***	1.3365***	1.2324***
	(0.0857)	(0.0909)	(0.0847)
lev	-1.0996***	-0.9926***	-1.3098***
	(0.3207)	(0.3276)	(0.3179)
roe	0.1513	0.0710	0.3153
	(0.2356)	(0.2407)	(0.2333)
inv	1.9134***	0.7866	1.2743**
	(0.6033)	(0.6053)	(0.6323)
fixed	-0.9358**	-1.1600**	-1.0124**
	(0.3922)	(0.4175)	(0.3975)
rec	5.1040***	5.1753***	4.8668***
	(0.7748)	(0.7877)	(0.7750)
board	1.2256**	1.2759***	1.1913***
	(0.2917)	(0.3028)	(0.2867)
top10	-2.2995***	-2.0849***	-0.9361**
	(0.4255)	(0.4369)	(0.4077)
mshare	-0.9012*	-0.6705	-0.3007
	(0.5101)	(0.5207)	(0.5063)
constant	-25.043***	-24.923***	-22.704***
	(1.9327)	(2.0465)	(1.9005)
Individual FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Industry FE	Yes		
Province×Year FE		Yes	
Industry×Year FE			Yes
Sample size	26746	26746	26746
F-test	36.611***	33.166***	31.083***
R^2	0.8372	0.8374	0.8453

Table 6: ROBUSTNESS CHECKS. Figures in parentheses are the robust standard errors. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$. This table presents regression results with alternative fixed effects, further validating the positive effect of the Fintech program.

	(1)	(2)
Independent \ Dependent	*rdinc*	*dinv*
did	0.0024**	0.7996***
	(0.0012)	(0.2114)
rdinc		9.5323***
		(1.5348)
size	0.0019***	1.4111***
	(0.0007)	(0.0890)
lev	-0.0037	-1.1181***
	(0.0026)	(0.3216)
roe	0.0091***	-0.0716
	(0.0016)	(0.2389)
inv	-0.0115***	1.1628*
	(0.0043)	(0.6025)
fixed	-0.0003	-1.2767***
	(0.0030)	(0.4039)
rec	-0.0271***	5.4569***
	(0.0048)	(0.7786)
board	0.0025	1.1575***
	(0.0020)	(0.2967)
top10	0.0333***	-2.7531***
	(0.0031)	(0.4380)
mshare	0.0022	-0.9679*
	(0.0032)	(0.5125)
constant	-0.0105	-26.278***
	(0.0155)	(2.0030)
Firm FE	Yes	Yes
Time FE	Yes	Yes
Sample size	26746	26746
F-test	26.568***	37.679***
R^2	0.7822	0.8343

Table 7: MEDIATION EFFECT REGRESSION RESULTS. Figures in parentheses are the robust standard errors. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$. This table reveals that the Fintech program enhances R&D intensity, which in turn partially mediates its impact on digital innovation.

	(1) High-Tech Firms	(2) Non-High-Tech Firms
Independent \ Dependent	*dinv*	*dinv*
did	1.0246***	0.2954
	(0.2704)	(0.2812)
size	1.4275***	1.3119***
	(0.1094)	(0.1415)
lev	-1.3420***	-0.0571
	(0.4307)	(0.4510)
roe	-0.2306	0.2029
	(0.2740)	(0.4021)
inv	2.5922***	-0.1906
	(0.9711)	(0.7388)
fixed	-2.3359***	0.8781
	(0.5012)	(0.7309)
rec	4.6967***	4.4468***
	(0.9404)	(1.2804)
board	1.2053***	1.0121***
	(0.3921)	(0.3618)
top10	-3.6586***	0.2460
	(0.5688)	(0.6444)
mshare	-1.7623***	1.2979*
	(0.6427)	(0.7780)
constant	-24.427***	-27.896***
	(2.4424)	(3.3048)
Individual FE	Yes	Yes
Time FE	Yes	Yes
Sample size	17,957	8,676
F-test	28.301***	13.673***
R^2	0.8461	0.7922

Table 8: HETEROGENEITY BY HIGH-TECH VS. NON-HIGH-TECH FIRMS. Figures in parentheses are the robust standard errors. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$. This table shows that the Fintech program has a stronger effect on high-tech firms compared to non-high-tech firms.

	(1) Eastern	(2) Central & Western
Independent \ Dependent	*dinv*	*dinv*
did	0.4984*	1.2419***
	(0.2809)	(0.3259)
size	1.6628***	0.7641***
	(0.1128)	(0.1324)
lev	-1.4047***	-0.0317
	(0.4138)	(0.4618)
roe	-0.1894	0.2811
	(0.2987)	(0.4031)
inv	0.3179	2.8381***
	(0.7393)	(0.9966)
fixed	-0.9241*	-2.0774***
	(0.5179)	(0.6347)
rec	5.8922***	3.5911***
	(0.9597)	(1.2916)
board	1.0722***	1.4402***
	(0.3819)	(0.4485)
top10	-2.3185***	-1.8676***
	(0.5521)	(0.6637)
mshare	-0.2124	-2.5184**
	(0.5958)	(0.9803)
constant	-30.592***	-14.318***
	(2.5373)	(3.0351)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Sample size	18,589	8,151
F-test	28.179***	10.249***
R^2	0.8353	0.8284

Table 9: REGIONAL HETEROGENEITY ANALYSIS. Figures in parentheses are the robust standard errors. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$. This table indicates that the impact of the Fintech program is more pronounced in central and western region than in eastern China.

Variable	Central & West − East	p-value
did	0.7430	0.0700
size	-0.8990	0.0000
lev	1.3730	0.0600
roe	0.4700	0.1900
inv	2.5200	0.0900
fixed	-1.1530	0.1600
rec	-2.3010	0.1600
board	0.3680	0.3000
top10	0.4510	0.3400
mshare	-2.3060	0.0200
constant	16.275	0.0000

Table 10: TEST FOR COEFFICIENT DIFFERENCES ACROSS GROUPS. This table shows the test results on the difference between the coefficients from different region, confirming regional heterogeneity.

	(1) High-Tech and Eastern	(2) High-Tech and Central & West	(3) Non-High-Tech and Eastern	(4) Non-High-Tech and Central & West
Independent \ Dependent	*dinv*	*dinv*	*dinv*	*dinv*
did	0.4564	1.8736***	0.3130	-0.0580
	(0.3667)	(0.3936)	(0.3568)	(0.4921)
size	1.6424***	0.7055***	1.4712***	1.0399***
	(0.1358)	(0.1650)	(0.1674)	(0.2777)
lev	-2.2315***	1.3532**	0.3761	-1.2893*
	(0.5585)	(0.5835)	(0.5629)	(0.7032)
roe	-0.5384	0.5470	-0.5220	-0.8884
	(0.3726)	(0.3565)	(0.3673)	(0.9884)
inv	2.6858**	1.9138	-2.3931***	4.8268***
	(1.2129)	(1.4344)	(0.7960)	(1.7462)
fixed	-1.9480***	-2.5936***	1.1992	-0.6369
	(0.6312)	(0.8254)	(0.9877)	(0.9096)
rec	5.6673***	2.5112*	6.1837***	-1.9420
	(1.1694)	(1.3628)	(1.4527)	(2.8195)
board	0.8905*	1.7368***	0.9645**	1.1914*
	(0.5166)	(0.5560)	(0.4339)	(0.6308)
top10	-3.9118***	-1.9278**	0.7877	0.0768
	(0.7262)	(0.8500)	(0.7602)	(1.1587)
mshare	-1.1706	-2.9512**	1.5892*	-0.1071
	(0.7504)	(1.1698)	(0.9016)	(1.5595)
constant	-27.143***	-13.377***	-31.582***	-21.677***
	(3.0381)	(3.7308)	(3.8735)	(6.6649)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sample size	12,589	5,343	5,926	2,749
F-test	20.325***	9.524***	12.091***	2.786***
R^2	0.8441	0.8523	0.8090	0.7500

Table 11: HETEROGENEITY ANALYSIS BY TECHNOLOGY AND REGION. Robust standard errors are in parentheses. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$. The results indicate that the Fintech pilot program has a significantly stronger effect on high-tech firms in central and western region.

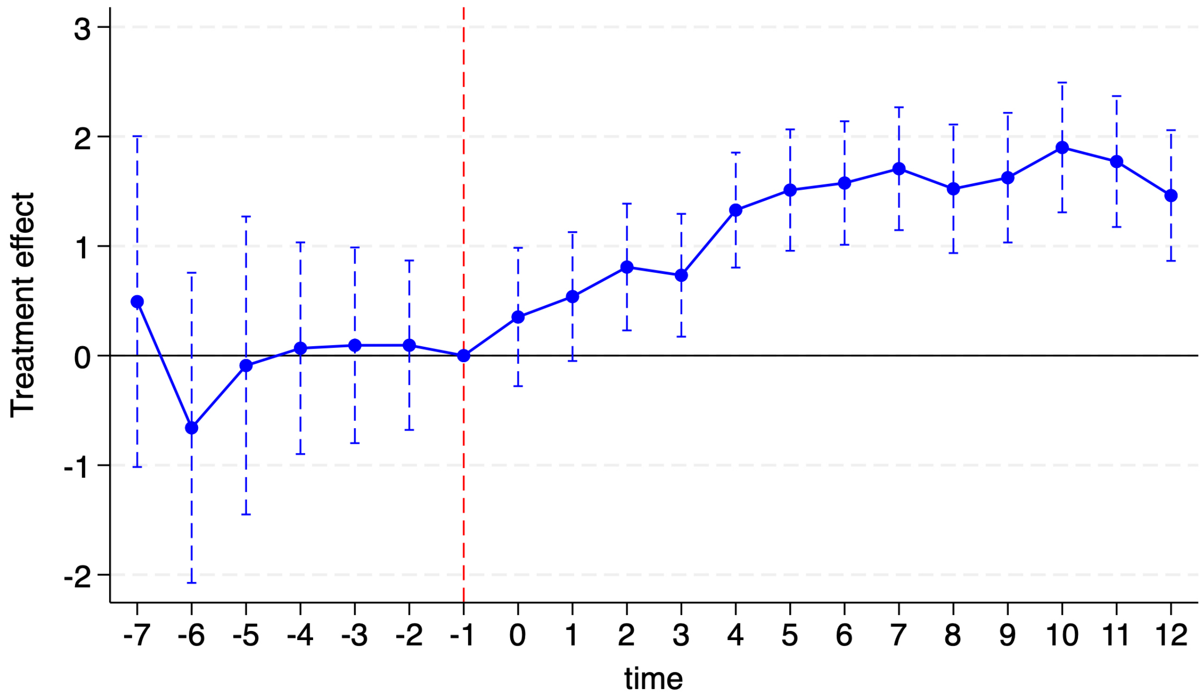

Figure 1: RESULTS OF THE PARALLEL TRENDS TEST. This figure confirms that the parallel trends assumption holds before implementing the Fintech program, supporting the validity of the DID design.

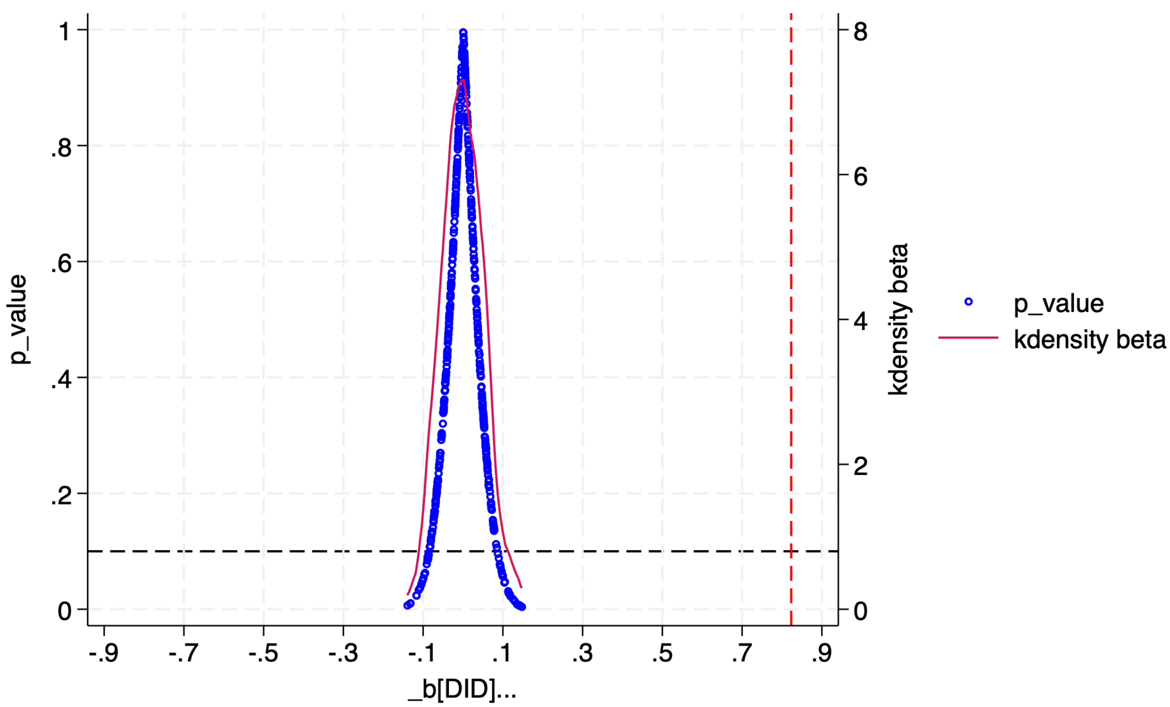

Figure 2: RESULTS OF THE PLACEBO TEST. This figure shows that the actual effect of the Fintech program lies far outside the distribution of placebo estimates, suggesting that the observed treatment effect is unlikely to be driven by random chance.

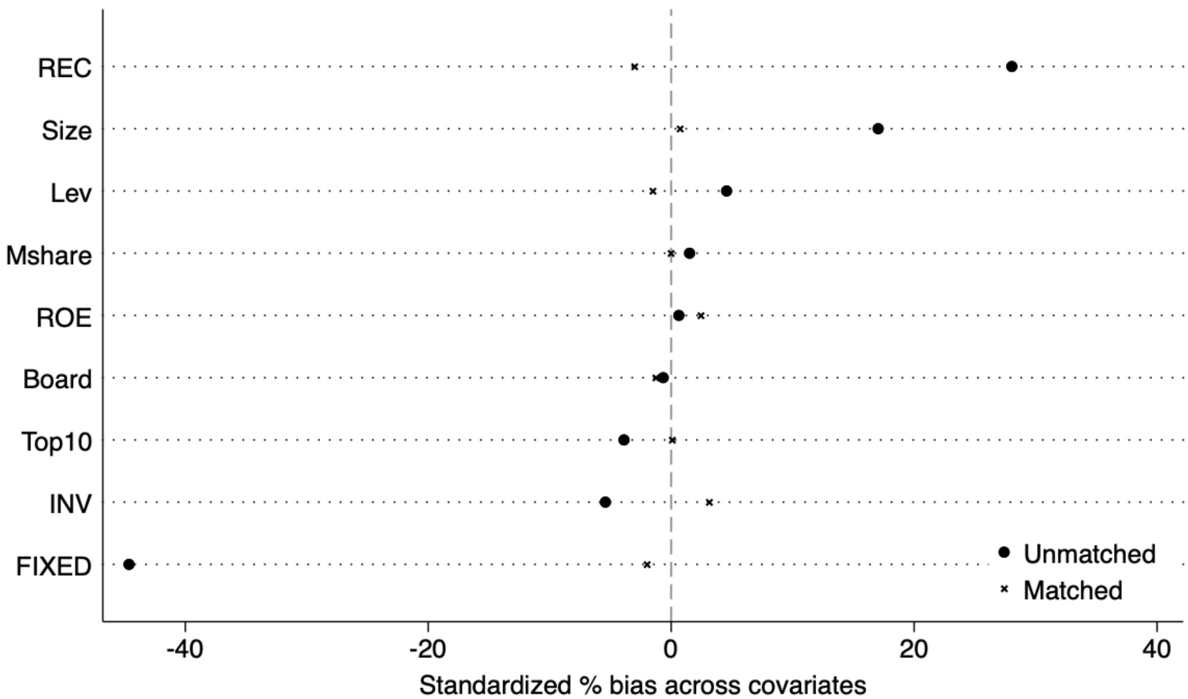

Figure 3: STANDARDIZED MEAN DIFFERENCES BEFORE AND AFTER MATCHING (HYBRID MATCHING). This figure plots the standardized mean differences (% bias) for each covariate before (solid dots) and after (crosses) mixed matching. After matching, all covariates lie close to the zero line, indicating that the treated and control groups are well balanced.

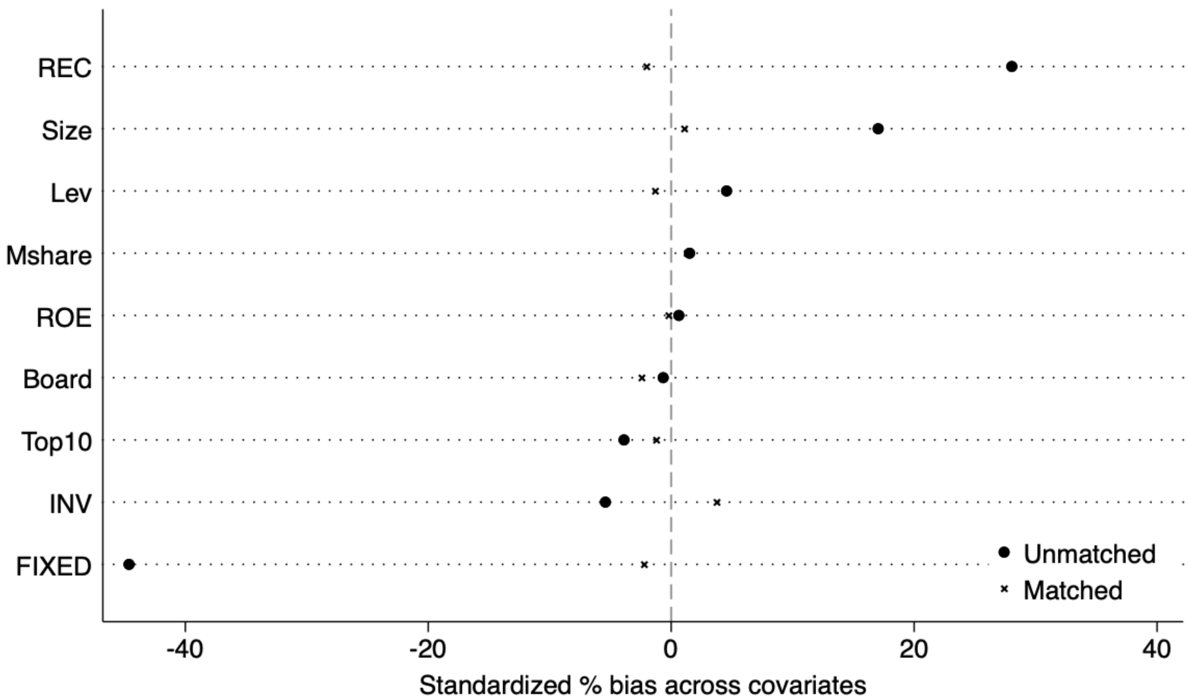

Figure 4: STANDARDIZED MEAN DIFFERENCES BEFORE AND AFTER MATCHING (YEAR-BY-YEAR MATCHING). This figure presents the standardized mean differences (% bias) across covariates under the year-by-year matching approach. The reduction in absolute bias values demonstrates that the matching procedure substantially improves the covariate balance for each year.