Digital Economy and Corporate Innovation-Washing
——An Empirical Study on How Information Mitigates Policy Distortion

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Abstract: *As stated in the Report to the 20th National Congress of the Communist Party of China (CPC), innovation remains at the heart of China's modernization drive, and it is vital to optimize the allocation of innovation resources, deepen structural scientific and technological reforms, and enhance the overall performance of China's innovation system. Government incentives have boosted firm R&D and innovation efforts; however, they have also triggered an innovation dilemma where enterprises, capitalizing on their informational advantages, resort to innovation-washing behaviors that undermine the intended purpose of the policies. Based on the information asymmetry theory, this paper conducts an empirical study on how the digital economy affects firms' innovation-washing behavior. The development of the regional digital economy could suppress firm innovation-washing behavior in the region, and such a mitigation effect is primarily caused by an increase in the number of digital industry professionals. According to our heterogeneity analysis, the digital economy has a greater impact on firm innovation-washing behavior for certain types of enterprises, including non-state-owned enterprises (non-SOEs), small and medium-sized enterprises (SMEs), enterprises in less competitive industries, and enterprises in unfavorable business environments. Our mechanism analysis revealed that the digital economy may restrain innovation-washing behavior by reducing information asymmetry between enterprises and external stakeholders. In terms of economic outcomes, the digital economy has the potential to directly influence firm innovation output while also indirectly mitigating the subsequent decline in innovation output by discouraging innovation-washing. This paper enriches the research findings on how the digital economy breaks down "information silos" and offers a potential solution to the "emphasis on input and quantity over quality and efficiency" phenomenon in science and technology innovation practices.*

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1. Introduction

The Report to the 20th National Congress of the Communist Party of China (CPC) called for

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“investing more effectively in science and technology and advancing reform of the mechanisms for the allocation and use of government research funds to inspire greater creativity”. Innovation activities result in significant positive externalities (Lach, 2002). Individual enterprises’ R&D activities generate knowledge and results that have the potential to spread to other enterprises and even sectors. To compensate for external losses, the government has issued industrial policy preferences to enterprises as a means of overcoming market failure (Gu and Shen, 2012). The Chinese government has implemented a number of policies that emphasize the importance of government innovation resources in fostering indigenous innovation (Zhang et al., 2016). Government fiscal subsidies and tax breaks are the most common ways to promote enterprise innovation and R&D (An et al., 2009).

However, Hall and Harhoff (2012) discovered that firms would use quantitative indicators as a strategic tool to demonstrate their innovation results to the government in exchange for policy support. In recent years, academics have conducted extensive research on firm innovation behavior under government incentives. They identified adverse selection behavior in which firms strategically maintained their R&D spending ratio around the innovation incentive policy criteria in order to meet the R&D subsidy threshold (Tong et al., 2014; Li and Zheng, 2016; Qiu, 2020). In other words, firms conduct R&D and innovation not to advance technology or improve products; rather, their R&D manipulation and innovation-washing behavior are intended to steal policy dividends (Yang et al., 2017; Cheng and Zhong, 2018; Sun et al., 2021; Zhang and Wu, 2022). Firm innovation behavior has seriously undermined the otherwise positive role of innovation incentive policy, leading firms to prioritize quantity over quality in order to gain policy support (Ying and He, 2022). Firms that overstated R&D spending to qualify for high-tech status had poorer R&D performance (Sun et al., 2021). Innovation-washing firms rarely achieved significant technological progress as expected by government policy (Wang et al., 2021), exacerbating the misallocation of government R&D resources and impeding firm innovation efficiency.

Notably, the majority of the research presented above focuses on the the differences in the manifestations of innovation incentive policies and the effects of their motivational impact. They not only provide strong justifications for the policy, but also rational discussions about why it failed, reaching some agreement while leaving many disagreements. In this context, recent academic research has shifted from discussions about “whether the innovation incentive policy works” to “how to alleviate firm innovation-washing behavior that counteracts government innovation incentive policy”. Despite preliminary research on this topic by Yang and Zhang (2021) and Dong et al. (2023), they failed to recognize the role of the digital economy in adjusting firm innovation-washing behavior. As a strategic choice for the next round of technological revolution, the digital economy happens to address information asymmetry as the root cause of opportunistic behavior in the implementation of the innovation incentive policy (Yang and Li, 2021). The digital economy supports the creation of an open, fair, just, and non-discriminatory industrial policy environment in the new era, allowing digital technologies to be used to empower the government, media, and other external governance forces (Chen and Hu, 2022). With its technological empowerment and data-driven features, the digital economy has greatly aided the development of new digital government, increased the efficiency of media supervision, and reduced information asymmetry between firms and external stakeholders. In this way, the digital economy has successfully regulated strategic firm behavior. One critical question remains regarding the effective implementation of China’s innovation-driven development strategy. That is, will the digital economy reduce firms’ innovation-washing behavior by promoting high-quality development, thereby overcoming the selection failure of the government’s innovation incentive policy? What is the context and path for the digital economy to exercise its influence? What are the economic outcomes of firm innovation? Academics have yet to conduct research on these theoretical and practical issues. As a result, the purpose of this paper is to conduct an empirical study to determine whether the digital economy can effectively mitigate innovation-washing behavior in order to recognize high-tech firms.

Based on the existing important research literature on the digital economy and firm innovation washing, we chose China's listed high-tech firms from 2008 to 2020 as research samples to discuss the impact of the digital economy on firms' innovation-washing behavior using the information asymmetry theory. Our research discovered that the development of a regional digital economy may reduce innovation-washing behavior among firms in the region, and this conclusion remains unchanged after a series of robustness tests. This mitigation effect is primarily caused by an increase in the number of digital industry professionals. We examined the heterogeneous effects of firm ownership type, firm size, level of industry competition, and business climate based on differences in the extent to which factors inside and outside the firms can influence the level of information asymmetry. Our mechanism test suggests that one of the ways the digital economy mitigates firms' innovation-washing behavior is to reduce information asymmetry between firms and external stakeholders. We also looked into the direct effects of the digital economy on firm innovation output, as well as the indirect effects of regulating firm innovation-washing behavior. Our findings offer more detailed theoretical support and recommendations for promoting the digital economy and implementing innovation incentive policies.

This paper's contributions are manifested in the following four areas: (1) "Enforcement" is an important step for industrial policy to play a role in resource allocation. However, some firms strategically manipulate their R&D input to meet the minimum threshold for applying for policy preferences. Such washing behavior has reduced the positive impact of government pro-innovation incentive policies, causing industrial policy implementation results to contradict policy intentions. This article focuses on the innovation-washing behavior in the recognition of high-tech firms, in contrast to current research on firm innovation-washing behavior, which focuses on "whether the effectiveness of government pro-innovation incentive policy will be distorted by firms and how such distortion occurs". The article believes that the digital economy can make it easier to access information during policy implementation, which will reduce fraudulent subsidy claims from "pseudo-high-tech firms" and give more weight to the positive role of pro-innovation incentive policy. As a result, our research on firm innovation through the lens of the digital economy is part of the research topic "How to ensure government incentive policies are effectively aligned with their intended objectives", echoing the view of some scholars that, while consensus may not be reached on the necessity of industrial policy, the key issue is to ensure effective industrial policy implementation (Dai and Cheng, 2019; Yang and Zhang, 2021; Ye et al., 2022). (2) To enrich our research and provide more in-depth empirical evidence, we have included firm ownership nature, firm size, industry competition level, and business climate in our study of the digital economy and firm innovation-washing behavior, resulting in a relatively complete research framework. The findings of our study offer a theoretical boundary for investigating the causal relationship between the digital economy and firm innovation-washing behavior. They also validate the "inclusive effect" of incremental supplement from the digital economy (Tang et al., 2020) and the significant role that inclusive industrial policy plays in mitigating market imperfections (Dai and Cheng, 2019; Ye et al., 2022). (3) Despite theoretical discussions about the digital economy's effect on reducing information asymmetry between firms and external stakeholders (Tang et al., 2020; Wan et al., 2020; Li et al., 2020), it is unfortunate that this mechanism has rarely been tested with large-sample data. With China's digital economy at the forefront of the global economy, this paper will examine the digital economy's underlying rationale for reducing firm innovation-washing behavior and conduct an empirical test of the intermediate effect of firm external information asymmetry. It also supports the use of information asymmetry theory in digital economy research, presents a new perspective on information-based regulation to mitigate firm innovation-washing behavior, and provides micro-level evidence that the digital economy enables high-quality firm development. (4) Existing research literature has found that the presence of firm innovation-washing behavior can be detrimental to independent firm innovation (Zhang, 2018), substantive innovation (Li and Zheng, 2016), and so on, but it has rarely investigated the digital economy's role in mitigating firm innovation-washing behavior. This paper develops a "digital technology + innovation" linkage system to investigate the effects of the digital economy on firm innovation output, including both direct and indirect effects through regulation of firm innovation-washing behavior. This setup is critical for establishing a digital economy development paradigm and promoting the effective implementation of innovation incentive policies.

This paper's remainder is organized as follows: A review of the literature is given in Section 2, the theory and hypotheses are discussed in Section 3, and the research design is introduced in Section 4. The results of the empirical test are reported in Section 5. Additional analysis is done in Section 6, and research findings are compiled and policy recommendations are made in Section 7.

2. Literature Review

Every country has, to varying degrees, adopted industrial policy throughout its history. Industrial policy, according to Yang and Hou (2019), is an incomplete contract between the government and businesses that takes into account all potential future events that neither the government nor businesses can predict and for which no third party can ensure effective contract enforcement. To put it another way, industrial policy has non-contractibility and externalities. This has caused the implementation of industrial policies to have such disparate effects that it is impossible for research in this area to come to widely accepted conclusions. For example, the *Administrative Measures for the Recognition of High-tech firms ("Administrative Measures")* seeks to promote firm investment and boost innovation output through a combination of tax incentives, government subsidies, and other policy tools. Scholars, however, have differed in their conclusions on this topic of research.

Regarding tax breaks, Bloom et al. (2002) discovered that tax incentives could boost firm R&D investment based on data from nine OECD countries. Through the intermediate effect of innovation input, Li et al. (2016) demonstrated that tax preferences would somewhat enhance firm innovation performance. Li (2018) also found that tax preferences would boost China's high-tech industries' R&D efficiency by 8% to 10%. Yang et al. (2017), however, argued that tax breaks had encouraged high-tech companies to manipulate R&D spending, using every possible tactic to be eligible for policy dividends instead of engaging in R&D in a serious manner. Additionally, Chen et al. (2021) confirmed that the innovation-washing behavior exists. They discovered that businesses would incorporate other costs into their R&D spending, and that tax preferences were the driving force behind this behavior. According to Sun et al. (2021), firm innovation-washing behavior limits the policy's implementation effect because the weighted deduction policy for R&D expenditure is susceptible to firm countermeasures.

In terms of R&D subsidies, Lu et al. (2014) and Yu et al. (2016) saw government subsidies as an important way to encourage firm innovation with significant policy implications. Shang and Fang (2021) discovered that government subsidies can boost firm technology innovation output by increasing risk tolerance. However, Li et al. (2017) discovered that, despite the above positive correlation, each unit increase in innovation subsidy resulted in an increase in firm innovation significantly smaller than 1. Zhang (2018) believed that government subsidies have a "crowd-out effect" because subsidized enterprises tended to purchase new technologies rather than innovate on their own. Furthermore, Mao and Xu (2015), Liu et al. (2019), and Wu and Zhang (2021) discovered that only a limited range of government subsidies could significantly incentivize enterprises to innovate, whereas large amounts of subsidies would inhibit firm innovation.

There have been ongoing debates about the effectiveness of industrial policies. Academics who support industrial policy effectiveness emphasized the importance of a capable government in industrial policymaking and market economies. They believed that the government could compensate for external R&D costs, effectively correct distorted efficiencies, and overcome market failure (Stiglitz et al., 2013; Lin, 2017). Proponents of industrial policy ineffectiveness argued that the above situations may assume that the government is immune to the problem of information asymmetry and the resulting incentive distortion, but in reality, the government finds it difficult to timely screen enterprises that are in real need of industrial policy support due to the high cost of collecting and identifying data. As a result, policy dividends are obtained by innovation-washing enterprises that engage in R&D manipulation, leading to the failure of industrial policy to achieve the desired effects (An et al. 2009). It is worth noting that, because industrial policy is a combination of selective industrial policy, functional industrial policy, and various types of policy instruments, an increasing number of scholars believe that discussions about how to make industrial policy more effective are as important as discussions about whether or not industrial policy should exist at all (Dai and Cheng, 2019; Yang and Zhang, 2021; Ye et al., 2022). In response to the aforementioned call, this paper seeks to expand on previous research on high-tech firms' innovation-washing behavior by Yang et al. (2017), Sun et al. (2021), Yang and Zhang (2021), and Dong (2023). The goal is to identify methods for reducing information asymmetry between firms and external stakeholders in order to maximize the positive impact of pro-innovation policies. In general, the government incurs significant time, human resource, and information costs in mitigating firm innovation-washing behavior, resulting in a resource mismatch of innovation incentive policy and compromising the policy's effectiveness. In the context of open and shared access to data amid the digital economy's rapid development, the cost to acquire data has been effectively reduced as a result of the non-competitiveness of digital products, the near-zero marginal cost of information, the online digital market without physical space, big data as a critical input, and other digital economy attributes (Zhang, 2022), putting opportunistic firm behavior under the supervision of a capable government and an efficient market. As a result, this paper will look into whether the digital economy will limit high-tech companies' innovation-washing behavior.

3. Research Hypotheses

According to classical economics, the market will achieve natural equilibrium under Adam Smith's "invisible hand". However, the prerequisite is quite stringent, requiring both parties or multiple parties to the transaction to have complete information, as well as all participants to have fully shared open market information. Indeed, there is a significant level of information asymmetry between the two sides of capital supply and demand (Yu et al., 2012). Cognitive limitations imply that the government is not always smarter than the market, and the problem of adverse selection caused by information advantage has become a major reason for some businesses to exploit government innovation incentive policies (Yang and Rui, 2020). To encourage independent firm innovation, the government has implemented a number of policy incentives, including fiscal subsidies, a weighted deduction of R&D spending from taxable income, and recognition of high-tech firms (Zhou and Lin, 2016; Chen, 2020). Firms, as complex and rational entities (Zhang and Zhao, 2008), may disguise themselves in order to obtain various policy preferences, and by manipulating R&D spending, send the government a false signal that they are capable of innovation, which is known as "innovation washing" (Bronzini and Iachini, 2014). They regard the use of innovation incentive policies as a way for businesses to evade taxes (Wan et al., 2020). Due to the high costs of information collection and discrimination,, the government, as the provider of policy incentives, is unable to promptly distinguish whether enterprises that meet the policy's hard thresholds are "true innovators" or "pseudo-innovators". This leads to government selection failure,, causing the incentive mechanism of industrial policies to become merely formalistic.

According to the information asymmetry theory, when external regulators such as governments and media organizations have limited and differentiated information about an enterprise, policy preferences will lead to government selection failure, resource misallocation, and a lack of media supervision, all of which seriously impede the effective functioning of innovation resources. However, in recent years, the digital economy, fueled by innovative technologies such as cloud computing, big data technology, and artificial intelligence (AI), has expanded the tools available to enterprises to mitigate external information asymmetry. These developments have significantly enhanced the information disclosure environment in the capital markets, effectively breaking the "information silo" dilemma and creating new opportunities to curb corporate behavior that accommodates innovation at the expense of transparency.

The digital economy provides a significant information advantage in overcoming the exclusivity of data via the internet. This enables the government to more directly trace real-time firm R&D status and identify firms in genuine need of industrial policy support and innovation vibrancy among a large number of applicants for fiscal preferences. In an environment with high information asymmetry, the government is unable to determine how R&D resources are distributed within the "black box" of enterprises. As a result, it can only decide whether or not to grant policy preferences to enterprises based on objective policy criteria. Then the enterprises are prompted to implement strategic countermeasures such as "image projects" that are unrelated to actual R&D activities (An et al., 2009), the application of a large number of low-quality patents (Zhang and Zheng, 2018), and the adjustment of accounting subjects to overstate R&D spending (Chen et al., 2021). This information dilemma has been reversed as the digital economy developed. On the one hand, the digital economy has the potential to significantly reduce the government's cost of searching for and identifying firm information through big data, cloud computing, and other data analysis tools, allowing it to identify and process an ocean of firm data in a low-risk and accurate manner (Demertzis et al., 2018; Gomber et al., 2018; Liu et al., 2023). Meanwhile, the digital economy has promoted data complementarity and synergy in a variety of business processes, presenting accurate business information. This enables the government and other stakeholders to learn about the real-time firm innovation process. When a company engages in dishonest innovation-washing behavior, it must not only manipulate internal information but also ensure data consistency across various processes. Otherwise, there is a greater risk that its misconduct will be exposed, resulting in reputational losses. In this case, the digital economy effectively addresses the government's challenge of integrating heterogeneous firm information. By increasing the cost of adverse selection, it discourages firms from obtaining policy preferences through innovation washing while incentivizing them to reflect their true level of innovation and needs. On the other hand, the digital economy has given rise to a variety of government information service platforms that have facilitated the exchange of business information and credit profiles between government agencies, thereby enhancing the precision, intelligence, and standardization of government regulation. This "dual online status" of the government and enterprises opens up the possibility of reducing information asymmetry between the two sides. It enables the government to track the progress of firm innovation in real time, thereby improving its weak information position, increasing its ability to penalize enterprises for innovation-washing behavior, and strengthening the contract spirit and contract execution capacity of both the government and enterprises. Furthermore, with lower information acquisition costs and increased administrative efficiency, the government is better able to pool and coordinate information from various enterprises and sectors to provide policymaking reference to maintain market order, adjust policy dynamics, and develop the digital economy, as well as regulate firms' tactical innovation behavior. In summary, the digital economy offers opportunities to fully extract additional information content, such as high-frequency data, non-structured data, and new structured data, using smart analytical technologies (Hong and Wang, 2021), allowing the government to obtain sufficient information that reflects a complete picture of enterprises and identify those masquerading as innovators in a timely manner.

The media, as an external governance avenue, plays an irreplaceable role in supervising firm behavior (Dyck et al., 2010; You et al., 2018). The media, as a critical vehicle of information communication, not only reveals firms' problems and misconduct and exposes negative incidents, but it can also promote their innovation and other activities that contribute to high-quality development (Wang and Zhang, 2021). In the midst of digitalization and AI revolution, the digital economy is transforming the original "pyramid structure" of information communication. Numerous disclosure instruments through the medium of mobile internet have effectively mitigated information quality attenuation and repeated internal concealment due to multi-link and multi-tiered communication loops. The reduction of information asymmetry between various market entities allows media organizations to more efficiently supervise and identify firms' misconduct, limiting their encroachment on pro-innovation policy dividends. To begin with, new digital technologies have improved the professional information collection and processing capabilities of news media, increasing the level and accuracy of media information disclosure (He and Liu, 2022). Media attention and reporting have a direct impact on a company's public image and market influence (Wu et al., 2022). In the digital economy era, new media have increased internet attention on enterprises, making them more sensitive to public opinion. With news coverage of firms' daily activities, particularly negative behavior, the management team is discouraged from interfering with company interests in order to protect the company image and their own professional reputation and avoid media exposure (Dyck and Zingales, 2004; Joe et al., 2009; Yang and Zhang, 2021). As a result, the digital economy may improve the efficiency of news media supervision, indirectly discouraging companies from using their insider information advantage to pursue self-interest. On the other hand, the digital economy offers a new mode for social media to proactively fulfill their supervisory functions, driving innovation in information transmission and supervision. Social media, led by Weibo and WeChat, have been fully empowered, demonstrating a strong governance effect. Their large user base, active user participation, and market influence have increased the temporal and spatial scope of information transmission, resulting in a "circle" effect of information flow (Chen and Hu, 2022). Social media, when combined with mobile internet and big data platforms, have the potential to "push" information to the public in a timely and straightforward manner, significantly simplifying the information collection process and lowering costs. More targeted information, once widely shared on social media, could reach a large number of investors (Xu and Chen, 2016), discouraging firms from engaging in pseudo-innovation activities and forcing them to regulate R&D activities, improve corporate governance, and reduce the space for corporate R&D manipulation.

Based on information asymmetry theory, we discovered that the digital economy may reduce the level of information asymmetry between firms and external stakeholders in terms of government review and media supervision, raising the cost of adverse selection, creating necessary conditions for the government to identify firms' innovation-washing behavior, and discouraging firms from engaging in innovation-washing behavior in order to receive policy preferences. As such, we propose Hypothesis 1:

Hypothesis 1: The digital economy may limit firms' innovation-washing behavior.

Hypothesis 2: The digital economy may limit firms' innovation-washing behavior by reducing information asymmetry between firms and external stakeholders.

4. Research Design

4.1 Variable Selection and Model Specification

4.1.1 Explained variable

The explained variable is the practice of firms' innovation washing (*Inca*). According to the

Chinese government's *Administrative Measures* enacted in 2008, enterprises are classified as having a sales income of less than 50 million yuan in the previous year, between 50 million and 200 million yuan, or more than 200 million yuan. These types of businesses must keep the current year's R&D expenditure to sales income ratio at no less than 6% (modified to 5% in 2016 and thereafter), 4%, and 3%, respectively. As a typical pro-innovation government policy document, the *Administrative Measures* prescribes clear screening standards that allow researchers to identify signs of R&D manipulation based on R&D spending ratios, and these standards have been extensively applied in relevant research on firm innovation-washing behavior. Using Sun et al.'s (2021) identification method and the R&D investment criteria specified in the Administrative Measures (amount of R&D spending/total operating income), we designate the 1% exceedance of the standard value as the boundary value, and the value is 1 if the ratio of R&D investment is no less than the standard value but smaller than the boundary value, or 0 if the ratio of R&D investment exceeds the boundary value. Except for the designated years, the value is 1 if the ratio is less than the standard value, and 0 if it equals or exceeds the standard value. If the value is 1, the enterprise is considered innovation-washing; otherwise, it is not.

4.1.2 Explanatory variable

The explanatory variable is the digital economy's development level (*Dige*). Using Zhao et al. (2020), we assessed the level of comprehensive digital economy development in cities with high-tech firms. The level of internet development is measured using four indicators: internet penetration, employment of industry practitioners, output level, and mobile phone penetration. These indicators include the number of internet users per 100 inhabitants, the percentage of the population employed in the computer services and software industry, total telecom business volume per capita, and the number of mobile phone users per 100 inhabitants. The Digital Inclusive Finance Index of Peking University, developed by the Task Force of Peking University's Institute of Digital Finance, indicates the level of digital inclusive finance. Finally, the principal component analysis is used to standardize and reduce the dimensions of the preceding five indicators, resulting in the Digital Economy Comprehensive Development Index for prefectural cities.

4.1.3 Intermediary mechanism variable

The degree of information asymmetry between firms and external stakeholders (*ASY*). Citing Yu et al. (2012), we developed an indicator for measuring the level of information asymmetry using daily frequency trading data to validate the intrinsic mechanism of information asymmetry between firms and external stakeholders. Yu et al. (2012) extracted the liquidity ratio *LR*, illiquidity ratio *ILL*, and the first principal component of the yield inversion indicator from the global asset management (*GAM*) to capture their asymmetric information components and create an information asymmetry indicator (*ASY*). With all other conditions constant, a higher level of information asymmetry results in a higher "lemon premium" requested by external non-informed traders to compensate for their information disadvantage. A higher level of stock liquidity correlates with a higher level of information asymmetry (*ASY*).

4.1.4 Controlled variables

Referring to Zhao et al. (2020), Zhang and Wu (2022), and Xie (2022), we identified the following firm-level control variables that may influence firm innovation behavior: Firm size (*Size*), solvancy (*Lev*), profitability (*Roa*), and firm age (*FirmAge*) are among the city-level control variables, along with the level of financial development (*Finde*), economic development (*Growth*), and foreign investment (*Fdi*).

Table 1 shows the variable definitions and measurements. To avoid interference from time, industry, and geographical factors, we added three dummy variables to the model: year (*Year*), industry (*Industry*), and province (*Province*).

Table 1: Variable Names and Definitions

Variable name	Variable symbol	Variable definition	Source of measurement literature
Innovation-washing behavior	*Inca*	Dummy variable: (1) The dummy variable is assigned a value of 1 if the ratio of R&D investment to total operating income is equal to or greater than the standard value in an identification year, and a value of 0 if it is equal to or greater than the boundary value. (2) The dummy variable is assigned a value of 1 when the ratio of R&D investment to total operating income is smaller than the standard value, and a value of 0 when it is equal to or exceeds the standard value, except for the identification year. The enterprise is deemed to have engaged in an innovation-washing activity when the assigned value is 1, while the enterprise is deemed to be free from any innovation-washing activity when the assigned value is 0.	Sun et al. (2021)
Development level of the digital economy	*Dige*	Uses the principal component analysis method to generate two indicators: the inclusivity of digital finance and the development of the internet. (1) Internet development: The number of internet users per 100 inhabitants, the total telecommunications business volume per capita, the proportion of the population employed in the computer services and software industry, and the number of mobile phone users per 100 inhabitants. (2) The inclusivity of digital finance: The Digital Inclusivity Finance Index of China.	Zhao et al. (2020)
Level of information asymmetry between firms and external stakeholders	*ASY*	Adopts principal component analysis to extract the liquidity ratio indicator *LR*, illiquidity ratio indicator *ILL*, and the first principal component of the global asset management (GAM) to generate the information asymmetry indicator (ASY). A greater degree of information asymmetry is indicated by a higher ASY.	Yu et al. (2012)
Firm size	*Size*	Natural logarithm of total assets at year end	Zhao et al. (2020) Zhang and Wu (2022) Xie (2022)
Solvency	*Lev*	Total liabilities at year end / total assets at year end	
Profitability	*Roa*	Net profit / Balance of total assets	
Firm age	*FirmAge*	Natural logarithm of years since establishment + 1	
Level of financial development	*Finde*	Balance of deposits and loans of financial institutions / regional GDP	
Level of economic development	*Growth*	Regional GDP growth rate	
Level of foreign investment	*Fdi*	Actual use of foreign capital in current year / regional GDP	
Year dummy variable	*Year*	Year dummy variable	
Industry Dummy variable	*Industry*	Industry Dummy variable	
Province dummy variable	*Province*	Province dummy variable	

Considering that our dependent variable is the dummy variable of innovation-washing behavior (*Inca*), we used the logit model for estimation, accounting for the fixed effects of year (*Year*), industry (*Industry*), and province (*Province*). Our regression equation is given below:

$$\text{Logit}(Inca_{i,t})=\alpha_0+\alpha_1 Dige_{i,t}+\alpha_2\sum Controls_{i,t}+\sum Year+\sum Industry+\sum Province+\varepsilon_{i,t} \qquad (1)$$

In equation (1), *Inca* is the firm innovation-washing tendency as the explained variable, *Dige* is the digital economy's development level, and *Control* is a collection of control variables that represent other control variables influencing firm innovation. The subscripts i and t denote the firm and year, respectively, and $\varepsilon_{i,t}$ represents the stochastic error term. If α_1 in the equation is significantly less than 0, it indicates that the digital economy's development level is negatively correlated with the firm's innovation-washing behavior, supporting hypothesis 1.

4.2 Data Source and Sample Selection

Current research on firm innovation-washing behavior uses high-tech companies as samples for the following reasons: First, high-tech firms, as a key driver of economic and technological innovation, require more R&D resources and benefit from government incentives (Zhang et al., 2019). Unlike the income tax rate of 25% for ordinary businesses, the *Administrative Measures* prescribe a 15% statutory income tax rate for high-tech businesses, allowing them to keep a 10% pretax profit, which is a significant amount. On the other hand, the *Administrative Measures*' "one-size-fits-all" threshold allows some manufacturing enterprises to engage in strategic innovation-washing activities. Because the "high-tech enterprise" title is required to obtain policy preferences, it is common for those enterprises to meet the minimum application criteria by manipulating R&D investment (Yang et al., 2017; Zhang and Wu, 2022), resulting in a false innovation signal that undermines the pro-innovation policy effect (Ying and He, 2022). According to existing research methodologies, we used *Administrative Measures* as an exogenous condition to determine the presence of firm innovation-washing behavior. As a result, we collected listed high-tech enterprise samples from the CSMAR database between 2008 and 2020, confirmed the missing data by reading annual reports, and compared them to the actual income tax rates of enterprises in the current year. Finally, we collected non-equilibrium panel samples from high-tech companies between 2008 and 2020. The relevant financial data and region-level variables used in this paper are all from the CSMAR and Wind databases. In particular, indicators for the development level of the digital economy (*Dige*) are derived from the China City Statistical Yearbook and the statistical yearbooks of specific prefectural cities. We conducted data screening and treatment using the following principles: (1) Exclude companies that halted public listing, delisted, and were subject to special treatment as marked ST and *ST; (2) exclude listed financial companies; (3) exclude enterprise annual samples with numerous missing values; (4) referring to Yang et al. (2017), exclude samples with fewer observations and sales income less than 50 million yuan from total samples; (5) we winorized continuous non-logarithmic variables at 1% to reduce the potential impact of extreme values on the results.

4.3 Descriptive Statistics and Correlation Analysis

Table 2 shows common descriptive statistical variable indicators. The mean value of innovation-washing behavior (*Inca*) in our samples is 0.228, implying that 22.8% of sample enterprises may have engaged in such activities. The digital economy's development level ranges from 0.002 to 0.891, indicating that it develops unevenly across regions. The minimum value of information asymmetry between firms and external stakeholders (*ASY*) is -1.129, while the maximum value is 1.003. According to the control variables, there are variations in firm size (*Size*), solvency (*Lev*), profitability (*Roa*), age (*FirmAge*), financial development levels across prefectural cities (*Finde*), economic development level (*Growth*), and level of foreign investment (*Fdi*).

Table 2: Descriptive Statistics

Variable	Observation values	Mean	Min.	25% quantile	Median value	75% quantile	Max.	Standard deviation
Inca	18201	0.228	0.000	0.000	0.000	0.000	1.000	0.420
Dige	16535	0.250	0.002	0.082	0.197	0.375	0.891	0.220
ASY	14743	-0.011	-1.129	-0.169	0.021	0.178	1.003	0.326
Size	14654	21.739	18.394	20.960	21.599	22.335	27.547	1.063
Lev	14654	0.356	0.042	0.202	0.341	0.491	0.820	0.187
Roa	14653	0.053	-0.208	0.022	0.052	0.086	0.224	0.062
FirmAge	14654	2.781	0.693	2.565	2.833	3.045	4.159	0.379
Finde	16530	1.547	0.406	1.046	1.566	2.015	3.054	0.607
Growth	14016	8.671	3.500	6.900	8.100	10.000	16.100	2.420
Fdi	16512	0.028	0.001	0.019	0.026	0.036	0.105	0.017

5. Regression Test and Empirical Results

5.1 Baseline Regression Results

Digital economy and firm innovation-washing behavior: Model (1) only includes the digital economy's development level as an independent variable (*Dige*) and the fixed effects of year, industry, and province, while model (2) adds other control variables based on model 1. The regression coefficients for the digital economy's development level in models (1) and (2) are -1.309 and -1.226, respectively, and both are statistically significant at the 1% level. This demonstrates how the digital economy can limit firms' innovation-washing behavior. In an economic sense, each unit of increase in the digital economy's development level in the logit model causes the ratio between the probability of firms' innovation-washing behavior and the probability of the non-existence of innovation-washing behavior (*Odds*) to be 0.293 times that of the original ($=e^{-1.226}$), and it can be calculated that the probability of firms' innovation-washing behavior has decreased by 14.9% based on the mean value of total-sample innovation based on the mean value of total sample innovation-washing behavior at 22.8% as the baseline[1]. In conclusion, the level of development in the digital economy will significantly reduce firms' innovation washing behavior in both statistical and economic terms, thereby verifying Hypothesis 1.

Table 3: Impact of the Digital Economy's Development Level on Firms' Innovation-Washing Behavior

Variable	(1)	(2)
	Inca	*Inca*
Dige	-1.309*** (0.162)	-1.226*** (0.233)
Size		0.202*** (0.029)
Lev		2.286*** (0.178)

[1] In total samples, the ratio between the probability of firms' innovation-washing behavior and the probability of the non-existence of innovation-washing behavior Odds=0.228/(1-0.228)=0.295. Each unit of increase in the digital economy's development level will cause the ratio between the probability of firms' innovation-washing behavior and the probability of the non-existence of innovation-washing behavior Odds to change to 0.086 ($=0.295\times e^{-1.226}$). That is, the probability of firms' innovation-washing behavior will change to 0.079, thereby reducing the probability of firms' innovation-washing activities by 14.9% (=|0.079-0.228|×100%).

Table 3 Continued

Variable	(1)	(2)
	Inca	*Inca*
Roa		1.183** (0.490)
FirmAge		0.425*** (0.077)
Finde		-0.246*** (0.069)
Growth		-0.012 (0.018)
Fdi		1.155 (1.760)
Year / industry / province fixed effects	Yes	Yes
Sample size	16531	10912

Note: *, **, and *** denote p-value significance at 10%, 5%, and 1% levels, respectively; coefficient values reported in the model are originally estimated values; and numbers in parentheses represent standard errors.

5.2 Robustness Test

5.2.1 Treatment effect model for correcting sample self-selection bias

This study may have an endogeneity problem due to the presence of a sample self-selection problem, which means that the chosen samples may not be random. For example, enterprises that proactively respond to and contribute to the development of the digital economy may exhibit less innovation-washing behavior, possibly due to unobservable traits of the city in which they are located, such as a culture of credibility (Tang et al., 2020; Ren and He, 2022) and social tolerance (Liu, 2022; Zhuang et al., 2022). These factors not only help the urban digital economy thrive, but they also attract businesses that are serious about innovation. To correct the samples' self-selection bias, we use a treatment effect model. We created the dummy variable of the digital economy's development level (*Dige dummy*) based on Zhou et al. (2022), which divides samples into two groups: high digital economy development (assigned value of 1) and low digital economy development (assigned value of 0). We adopt the interaction term between the number of telephones per 100 inhabitants in 1984 and the number of nationwide internet users in the previous year as the first instrumental variable (IV1) (Huang et al., 2019), the interaction between land relief of various cities and the number of internet users in the previous year as the second instrumental variable (IV2) (Nie and Pan, 2023), and the natural logarithm of the per capita number of broadband internet access ports (number of broadband internet access ports / number of population in the region at year end) as the third instrumental variable (IV3) (Deng et al., 2021) to mitigate the sample selection problem. In models (1), (3), and (5), we performed a probit estimation of the dummy variable representing the digital economy's development level (*Dige dummy*) and introduced the above exogenous instrumental variables while controlling for the original control variables. Table 4 shows the results of the treatment effect model. The Wald test results are all significant, indicating the presence of an endogeneity problem that requires sample selection bias to be corrected. In models (2), (4), and (6), the regression coefficients for the dummy variable representing the digital economy's development level (*Dige dummy*) remain significantly negative. This suggests that, even after accounting for the possibility of sample self-selection bias, the level of digital economy development continues to have a significant inhibitory effect on firms' innovation-washing behavior.

Table 4: Treatment Effect Model

Variable	Selection equation (Stage 1)	Treatment equation (Stage 2)	Selection equation (Stage 1)	Treatment equation (Stage 2)	Selection equation (Stage 1)	Treatment equation (Stage 2)
	(1)	(2)	(3)	(4)	(5)	(6)
	Dige dummy	*Inca*	*Dige dummy*	*Inca*	*Dige dummy*	*Inca*
Dige dummy		-0.599^{***} (0.158)		-0.462^{**} (0.168)		-0.484^{***} (0.169)
IV1	0.000^{***} (0.000)					
IV2			-0.000^{***} (0.000)			
IV3					0.673^{***} (0.070)	
IMR		0.216^{**} (0.106)		0.104 (0.108)		0.121 (0.108)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year / industry / province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Wald test	12.027^{***}		3.310*		124.066***	
Sample size	7578	7578	7923	7923	7923	7923

Note: Same as Table 3.

5.2.2 External event shock: Policy context of the "National Big Data Comprehensive Pilot Zones" and difference-in-differences (DID) model

In 2015, the State Council issued the *Circular on the Promulgation of the Outline of Actions for the Promotion of Big Data Development*, which explicitly called for accelerated big data development. In September of the same year, Guizhou Province took the lead to initiate the development of the big data pilot zone. In 2016, the National Development and Reform Commission (NDRC), the Ministry of Industry and Information Technology (MIIT), and the Office of the Central Cyberspace Affairs Commission successively officially approved the establishment of eight big data pilot zones, including Guizhou Province, Beijing-Tianjin-Hebei Region, the Pearl River Delta region, and Shanghai Municipality. Qiu and Zhou (2021) and Sun et al. (2023) both believed that the National Big Data Comprehensive Pilot Zones could represent the digital economy's development because they helped integrate regional big data infrastructures and pool data resources. Furthermore, we calculated the differences in the mean Digital Economy Index values for demonstration and non-demonstration cities before, during, and after 2015 to validate the relationship between the establishment of the National Big Data Comprehensive Pilot Zones and the level of digital economy development. According to the t-test results in Table 5, demonstration cities saw an increase in the level of digital economy development in 2015 and thereafter when compared to non-demonstration cities. We used a DID model with high-tech firms from 2008 to 2021 as research samples to see if the establishment of National Big Data Comprehensive Pilot Zones inhibited firms' innovation-washing behavior, referring to Sun et al. (2023). According to Guo et al. (2022), we assigned a value of 1 to demonstration cities in Guizhou Province since 2015 and demonstration cities in other provinces since 2016, and designated the year preceding the establishment of demonstration cities as the baseline year. Prior to conducting regression analysis, we used the event analysis method to validate the parallel trend hypothesis, as illustrated in Figure 1. Prior to the establishment of the big data comprehensive pilot zones, the policy dummy variable's estimated coefficients are all insignificant for all periods, indicating that there is no significant difference between demonstration and non-demonstration cities. Innovation-washing behavior in demonstration cities decreased over time following policy implementation. This implies a lag and dynamic continuity of the policy effect, which supports the parallel trend hypothesis. Finally, regression results in Table 6 show that the coefficient for establishing national big data comprehensive pilot zones (*DID*) is significantly negative, indicating that the baseline model's estimated results are reliable.

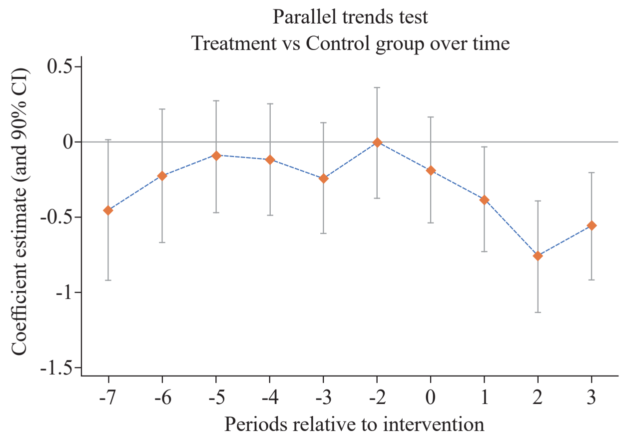

Figure 1: Parallel Trend and Dynamic Effect Chart (90% Confidence Interval)

Table 5: T-Test of the Digital Economy's Development Level in Demonstration and Non-Demonstration Cities Before and After 2015

Period	Grouping	Observation values	Level of economic development (*Dige*)	t-value	Difference and significance of mean value
Before 2015	Demonstration cities	3151	0.324	36.003	0.185***
	Non-demonstration cities	3308	0.139		
2015 and thereafter	Demonstration cities	4894	0.346	40.700	0.161***
	Non-demonstration cities	5182	0.185		

Table 6: External Event Shock

Variable	(1)
	Inca
DID	-0.331***
	(0.104)
Control variable	Yes
Year / industry / province fixed effects	Yes
Sample size	10556

Note: Same as Table 3.

5.2.3 T-Test

We then used the t-test as a parametric hypothesis test and grouped the digital economy's development level by median value to see if there was a significant difference between the inter-group samples. First, we used data from the baseline regression to see if there was a decrease in the number of enterprises identified as engaging in innovation-washing behavior but still recognized as eligible at various stages of the digital economy's development. According to the results presented in Table 7, significantly fewer samples in the group with a higher level of digital economy development were eligible through innovation-washing activities than those in the group with a lower level of digital economy development. First, we observed that some enterprises had experienced eligibility interruptions, which we believe were caused in part by more stringent government supervision. As a result, we used data from high-tech firms established between 2008 and 2021 to determine whether there is a difference in the average time of interruption in firm eligibility due to the differentiated effects of the digital economy's development level. According to the findings in Table 8, the average duration of interruption is significantly longer for the group with the highest level of digital economy development than for the group with the lowest level of digital economy development. In conclusion, the test results provide indirect support for Hypothesis 1: The level of regional digital economy development may have a direct impact on the eligibility of high-tech firms.

Table 7: T-test for Samples Having Obtained Eligibility through Innovation-washing Activities under the Digital Economy's Influence

Grouping	Observations	Average count of innovation-washing behavior	t-value	Mean difference and significance
Low Dige	8273	0.291	16.158	0.106^{***}
High Dige	8262	0.185		

Table 8: Sample T-test for the Duration of Eligibility Interruption under the Digital Economy's Influence

Grouping	Total number of subjects	Total number of records	Total number of interruptions	Average duration of subject interruptions	Difference and significance of mean value
Low Dige	1865	2616	242	3.643	-0.199^{***}
High Dige	1014	1862	135	3.841	

5.2.4 Measurement method of variable replacement

For independent variables, the preceding section used Zhao et al.'s (2020) comprehensive index to assess the level of development of the digital economy. Furthermore, Bukht and Heeks (2017) believed that the digital economy should encompass digital infrastructure, digital industrialization, and industrial digitalization. As a robustness test[2], we replaced our independent variable with the digital industry's business volume as an indicator for measuring digital industrialization (*Digital*, unit: 10,000 yuan per person). The data are from China's Statistical Yearbook of Science and Technology. Table 9 shows the regression results for model (1).

The dependent variable, innovation-washing behavior, is defined in the preceding regression test as precisely meeting the R&D investment ratio of 1% (amount of R&D investment / total operating income) as specified by the *Administrative Measures*. To avoid potential measurement errors, we replaced the method for measuring the dependent variable. First, using Sun's (2021) robustness test method, we adjusted the boundary value as 0.5% above the R&D spending specified in the *Administrative Measures*, and the regression results are shown in model (2) in the table. Second, according to Yang et al. (2017), *Inca2* is assigned as 1 if the total operating income is less than 200 million yuan and the ratio of firm R&D spending to total operating income is within the range of [4.0%, 5.0%), or 0 if otherwise. *Inca2*

[2] We appreciate the valuable comments from review experts.

is defined as having a total operating income of at least 200 million yuan and a ratio within the range of [3.0%, 4.0%), or 0 if otherwise. The regression results are shown in model (3) of Table 9.

In summary, results in Table 9 suggest that both the regression coefficient and significance of the key variables support our Hypothesis 1, and our core conclusions remain unchanged.

Table 9: Robustness Test after the Replacement of Variable Measurement Method

Variable	(1)	(2)	(3)
	Inca	*Inca1*	*Inca2*
Dige		-1.232*** (0.251)	-0.680*** (0.205)
Digital	-0.286*** (0.082)		
Control variable	Yes	Yes	Yes
Year / industry / province fixed effects	Yes	Yes	Yes
Sample size	10143	10912	10867

Note: Same as Table 3.

5.3 Heterogeneity Analysis

There could be heterogeneity in the digital economy's inhibiting effect on firm innovation due to the intrinsic characteristics and external environment of firms, which will be discussed in this section.

First, non-SOEs have a greater preference to meet the threshold of innovation incentive policies by means of R&D manipulation (Yang et al., 2017). This is because , compared to the "political genes" inherent in state-owned enterprises, non-state-owned enterprises face greater challenges in accessing policy benefits. (Allen et al., 2005). Meanwhile, the authenticity of non-financial information disclosed by non-SOEs cannot be guaranteed (Shen et al., 2010; Li et al., 2020). The digital economy could accurately capture the actual performance of non-SOEs by means of various digital media, thereby playing a greater role in supervising and curbing non-SOEs' innovation-washing behavior.

Second, some small and medium-sized enterprises (SMEs) are fundamentally motivated by government R&D subsidies to conduct innovation due to their limited capital and technological capabilities (Kang, 2018). In contrast, it is easier for large enterprises to draw attention from regulators. Therefore, the management of large enterprises could be less inclined to engage in opportunistic behavior than SMEs due to the importance to protect their business legitimacy and reputation. Coordinated management in the digital economy may enhance internal and external supervision and check and balance for SMEs, reduce hidden information about the management, and thereby magnify the marginal effect that restrains SMEs' innovation-washing behavior.

Third, market signal and government signal jointly influence firms' innovation decisions (Xia and Huang, 2019). In a low industry competition environment, the lack of benchmark effect of homogeneous competition has exposed firms to a more severe problem of information asymmetry, aggravating the selection bias of industrial policy (Li and Zheng, 2016). Rapid information communication in the digital economy may help firms swiftly know about the actual business performance of their competitors, prompting them to make greater efforts to catch up with overall market development level, pursue indigenous innovation, and refrain from innovation-washing behavior that send a false signal.

Lastly, an inadequately developed business environment will, to some extent, induce improper performance of firms (Xia et al., 2019). Inadequate law enforcement and high cost of information search have led to the absence of substantive government review. Media reports on corporate legal violations often lack credibility, which makes it difficult to effectively oversee businesses. Creating a digital business environment for the new era offers a crucial solution to the problem of information asymmetry in both economic and social contexts (Ding et al., 2024), and discouraging firms from resorting to illegitimate compensation by raising the opportunity cost of moral hazard.

Based on the above discussions, we conducted a grouped regression using for situational variables that may influence information asymmetry, including company ownership nature (measured by whether a company's actual controller is an SOE, and the value is 1 if so, or 0 if not), the level of industry competition (measured by the market share of the top four companies and grouped by median values, with the high-competition group assigned the value of 1 and the low-competition group assigned the value of 0), and the level of business environment (measured by the city comprehensive economic competitiveness in the China City Competitiveness Report, with the high business environment assigned the value of 1 and the low business environment assigned the value of 0). Test results are shown in Table 10. In Table 10, *Dige*'s regression coefficient is more significant for the non-SOE group according to columns (1) and (2). *Dige*'s regression coefficient is more significant for SMEs according to columns (3) and (4). *Dige*'s regression coefficient is more significant for less competitive industries according to columns (5) and (6). *Dige*'s regression coefficient is more significant for worse business environment according to columns (5) and (6). In summary, the digital economy's inhibiting effect on firms' innovation-washing behavior is more significant for non-SOEs, SMEs, enterprises in less competitive industries, as well as enterprises in a less favorable business climate.

Table 10: Test of Heterogeneity Analysis

Variable	Non-SOEs	SOEs	SMEs	Large enterprises	Less competitive industries	More competitive industries	Unfavorable business climate	Favorable business climate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Inca	*Inca*	*Inca*	*Inca*	*Inca*	*Inca*	*Inca*	*Inca*
Dige	-1.568***	0.568	-1.534***	-1.008***	-1.230***	-0.975**	-2.378***	-0.512
	(0.267)	(0.551)	(0.334)	(0.341)	(0.297)	(0.396)	(0.546)	(0.374)
p-value for testing inter-group difference	chi2(1)=24.137 Prob>chi2=0.000		chi2(1)=4.965 Prob>chi2=0.0260		chi2(1)=38.003 Prob>chi2=0.000		chi2(1)=7.752 Prob>chi2=0.005	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year / industry / province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	8572	2297	5763	5103	5620	5190	5876	3453

Note: p-value for testing inter-group difference is used to test the significance of *Dige* coefficient between various groups, and is obtained with the Chow test method. Others are the same as Table 3.

5.4 Mechanism Analysis

According to the preceding analysis, theoretical explanations for the relationship between the digital economy's development level and firms' innovation-washing behavior are primarily based on information asymmetry between firms and external stakeholders. To validate Hypothesis 2, we conducted an empirical analysis of the information asymmetry mechanism.

In recent years, some scholars have pointed out that the traditional three-step method for testing intermediate effects may result in an endogeneity problem with the intermediate variable (Jiang, 2022). To address the potential endogeneity issue, we corrected the intermediate variable with one- and two-phase lags. Table 11 shows how the digital economy influences firms' innovation-washing behavior by reducing information asymmetry between firms and external stakeholders. Model (1) is consistent with the preceding section, validating that the digital economy's growth may impede firms' innovation-washing behavior. In model (2), there is a significantly negative correlation between the digital economy's development level and the level of information asymmetry at 10%, implying that the digital economy's development is indeed conducive to reducing the level of information asymmetry between firms and external stakeholders. After incorporating the information asymmetry degree variable, model (3) shows that the regression coefficient of the digital economy's development level is significant at the 5% level, indicating that a decrease in the level of information asymmetry is one of the intrinsic mechanisms by which the digital economy's development inhibits firms' innovation-washing behavior. Our hypothesis H2 has thus been validated. To ensure the robustness of our conclusions, we used the intermediate effect test method. The structural equation model (SEM) can solve the problem of not being able to obtain a causal relationship through correlation analysis and distinguishing between direct and indirect effects. The generalized structural equation model (GSEM) can be used in situations where the results or intermediate variables are non-continuous (binary, ordinal, counting, etc.). As such, we used the GSM to supplement the mechanism test. The results show that the indirect effect is significant at 5%, implying that the mechanism of information asymmetry exists.

Table 11: Mechanism Test of Information Asymmetry between Firms and External Stakeholders

Variable	(1)	(2)	(3)
	Inca	*ASY*	*Inca*
Dige	-1.226^{***} (0.233)	-0.046^{*} (0.027)	
L2.Dige			-0.691^{**} (0.330)
L.ASY			0.726^{***} (0.159)
Control variables	Yes	Yes	Yes
Year / industry / province fixed effects	Yes	Yes	Yes
GSEM test (Z value)	-2.080^{**}		
Sample size	10912	10868	7125

Note: Same as Table 3.

This paper argues that the development of the digital economy influences firms' innovation-washing behavior, with the alleviation of information asymmetry serving as the key mechanism. Here, we present empirical evidence to support this proposed mechanism. Given that our theoretical explanations have elucidated the digital economy's role in reducing information asymmetry from the two perspectives of government administration and media supervision, it is imperative to directly evaluate the impact of the digital economy on the innovation-washing behavior of firms from the perspectives of government efficiency and media supervision[3]. We selected the primary indicator of government performance as an intrinsic effect variable for government efficiency (*Efficiency*) in accordance with the composite indicator for measuring local governance capabilities developed by Wu and Wu (2022). The entropy evaluation method is employed to determine the weights of two secondary indicators, fiscal spending and administrative efficiency, which are used to assess government performance. The statistical yearbooks for various provinces contain relevant research data. The level of media attention (*Tmedia*) is measured

[3] We appreciate the valuable comments from review experts.

by the number of media news reports, as per Wang et al. (2021). Given that online media serve as the primary medium for disseminating information to the general public, we measured the extent of media attention by dividing the annual total number of network media reports by the natural logarithm. The CNRDS database for various provinces contains relevant research data.

Table 12 displays the regression results. The mechanisms by which the digital economy's development inhibits firms' innovation-washing behavior by increasing government efficiency and media attention have been tested in Models (2), (3), (4), and (5), respectively. The digital economy's development is indeed conducive to increasing government efficiency and media attention to firms, as indicated by Models (2) and (4). Models (3) and (5) have confirmed that the digital economy inhibits firms' innovation-washing behavior through the intrinsic mechanisms of government efficiency and media attention.

Table 12: Mechanism Test of Government Efficiency and Media Attention

Variable	(1)	(2)	(3)	(4)	(5)
	Inca	*Efficiency*	*Inca*	*Tmedia*	*Inca*
Dige	-1.226*** (0.233)	0.052*** (0.004)		0.154* (0.090)	
L2.Dige			-0.776** (0.317)		-0.725** (0.330)
L.Efficiency			-2.719** (1.384)		
L.Tmedia					-0.089** (0.044)
Control variables	Yes	Yes	Yes	Yes	Yes
Year / industry / province fixed effects	Yes	Yes	Yes	Yes	Yes
GSEM test (Z value)		-1.766*		-1.656*	
Sample size	10912	10552	7708	10696	7121

Note: Same as Table 3.

6. Further Analysis

6.1 Dimension-by-Dimension Test of the Digital Economy's Development Level

Please see Table 13 for the five dimensions of how the digital economy's development may affect firms' innovation-washing behavior. Obviously, internet penetration (*Internet*), the employment of relevant personnel (*Employee*), relevant output (*Service*), mobile phone penetration (*Phone*), and the development of digital finance (*Findex*) all significantly inhibit firms' innovation-washing behavior. Furthermore, model (6) reveals that only the employment of relevant personnel (*Employee*) has a negative coefficient. One possible explanation is that, as stated in the *Research Report on China's Digital Economy Employment Development 2020*, digital industry practitioners, as a pillar of digital economy development, play an important role in advancing the internet development process. Digital industry practitioners are skilled not only in artificial intelligence (AI), computer algorithms, and other disruptive digital skills, but also in fundamental digital skills such as computer network and software testing, which serve as the foundation of online technology R&D and software platform development. In this sense, the digital economy has created a demand for a variety of digital industry jobs. Technological change opens up possibilities for reducing information asymmetry between firms and external stakeholders, allowing the government, media organizations, and regulators to discourage firms' innovation-washing behavior.

Table 13: Dimension-by-Dimension Robustness Test of the Digital Economy's Development Level

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Inca	*Inca*	*Inca*	*Inca*	*Inca*	*Inca*
Internet	-0.005***					-0.003
	(0.001)					(0.002)
Employee		-11.598***				-10.159***
		(2.262)				(2.460)
Service			-0.000***			-0.000
			(0.000)			(0.000)
Phone				-0.001***		-0.000
				(0.000)		(0.000)
Findex					-0.012***	-0.004
					(0.003)	(0.004)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year / industry / province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	10868	10911	10911	10899	10143	10101

Note: Same as Table 3.

6.2 Analysis of Economic Outcomes

The preceding analysis revealed the digital economy's inhibiting effect on firms' innovation-washing behavior, as well as the situational effect and impact pathway. This section, based on Dong et al. (2023), investigates the direct impact of the digital economy on firms' innovation-washing behavior as well as the indirect effect on firms' innovation output. Given the time lag between patent application and acquisition, the number of patent applications provides a more accurate measure of a company's innovation performance in the current year (Ying and He, 2022). As a result, we use the number of firms' invention patent applications in the current and future one phases as a measurement indicator for Poisson regression estimation. Table 14 illustrates the digital economy's impact on firm innovation output. The coefficients of digital economy development in the first two rows (*Dige*) are significantly positive, while the coefficient of firms' innovation-washing behavior (*Inca*) is negative. This demonstrates that, in addition to directly increasing the number of firms' innovation patent applications, the digital economy's development may indirectly increase firms' innovation output by reducing innovation-washing behavior.

Table 14: Economic Outcomes and Analysis

Variable	Innovation output in the current phase		Innovation output in the future one phase	
	(1)	(2)	(3)	(4)
Dige	0.808***	0.788***	0.627***	0.599***
	(0.018)	(0.018)	(0.018)	(0.018)
Inca		-1.112***		-0.844***
		(0.007)		(0.007)
Control variables	Yes	Yes	Yes	Yes
Year / industry / province fixed effects	Yes	Yes	Yes	Yes
Sample size	10913	10913	9663	9663

Note: Same as Table 3.

7. Research Conclusions and Policy Recommendations

7.1 Research Conclusions

The *14th Five-Year Plan for the Development of the Digital Economy*, which was released in January 2022, emphasizes the digital economy's critical role in unlocking China's economic dynamism. Enterprises participate in and benefit from the development of the digital economy. It is unclear whether the digital economy will discourage their innovation-washing behavior, which has plagued the governments. Using listed high-tech firms from 2008 to 2020 as research samples, we first investigated the digital economy's impact on firms' innovation-washing behavior through the lens of information asymmetry theory, and then tested the situational effect, mechanism, and economic consequences of the digital economy's role in discouraging firms' innovation-washing behavior. Our goal is to identify a path for government policy incentives to address firms' innovation-washing dilemma. Our primary research conclusions are as follows: The growth of a regional digital economy has significantly reduced firms' innovation-washing behavior in the region. This conclusion proves true after several robustness tests. It was also discovered that this effect is primarily caused by an increase in digital industry professionals. The digital economy has a greater inhibitory effect on firms' innovation-washing behavior for non-SOEs, SMEs, enterprises in less competitive industries, and enterprises in a less favorable business environment. Reducing the information asymmetry between enterprises and the external environment is one way that the digital economy prevents firms from washing their innovations. The digital economy has a direct impact on firms' innovation output, but it may also indirectly mitigate the subsequent decline in innovation output by mitigating firms' innovation-washing behavior.

7.2 Policy Recommendations

First, various levels of government must steadfastly advance the development of the "Digital China Initiative", facilitate information transmission for social and economic development, and ensure the proper flow of various factors. Meanwhile, the government should promote the digital economy's role in spearheading industrial development, encourage innovation as the primary driving force, and consolidate the numerous benefits that information technology provides to ensure the effective implementation of innovation incentives. Notably, the true value of big data comes from data analysis, and information users should focus on data value rather than data itself. Given that financial data cannot provide a complete picture of enterprises, it is proposed to use machine learning and risk control model to learn about firms' R&D dynamics and innovation quality in real time, as well as to improve eligibility review for high-tech firms, focusing on those with R&D intensities suspected of manipulation under the *Administrative Measures,* in order to effectively prevent and detect innovation-washing behavior.

Second, the digital economy should fully empower the government, media, and other regulatory agencies to break down information barriers between businesses. The government should use digital technology to improve government services, streamline administrative review and approval, and move away from a siloed work style toward cross-departmental collaboration. This shift is not only the government's self-adjustment to the digital economy, but it is also an obvious choice for leveraging the government's role in reducing firms' adverse selection behavior. While the government has the authority to initiate administrative review and approval, other governance mechanisms, such as media supervision, must be implemented in order to concentrate the forces of various private actors, expand the coverage of government services, and ensure coordination, mutual benefit, and interconnectivity between government and market mechanisms. Proactive efforts should be made to improve facilities and human resources to help the digital economy thrive. It is suggested that digital platforms be linked to mobile Internet to broaden the information boundary, that official government accounts be set up on various social media platforms to track public opinion, that big data be integrated with social management, and that innovation incentive policies be promoted for their positive role.

Third, it is suggested to implement a differentiated digital economy development strategy based on the needs of businesses and communities, as well as to integrate digital technology with the real economy. On the one hand, non-SOEs and SMEs are critical drivers of economic development, contributing significantly to innovation and economic growth. When developing the digital economy, the government should prioritize non-SOEs and SMEs to maximize their inhibitory effect on firms' innovation-washing behavior. On the other hand, it is critical to create an external environment conducive to the development of the digital economy, with "digital intelligence" serving as a key driver. Government at all levels should encourage high-quality firm innovation, build corporate credibility and key financial information databases, improve science-based legislative systems, and provide adequate development space for various market entities in terms of market access, review and approval, R&D innovation, and other issues. In the post-COVID-19 era, the digital economy's ability to transmit information and provide shared access across time and space will be critical to the modernization of the national governance system.

Fourth, given that preferential tax policies led by the *Administrative Measures* have yet to play a more positive role in supporting the digital economy's development, it is suggested to implement differentiated innovation incentive policies based on the local development levels of the digital economy, as well as to establish preventive and punitive systems for "pseudo-innovations" through which enterprises fraudulently claim policy subsidies. For example, Cheng and Zhong (2018) and Ying and He (2022) proposed implementing "ex-post review" allowance systems such as "technology vouchers" and increasing screening of corporate innovation outcomes. According to Sun et al. (2021), government fiscal allowances can provide promising companies with an opportunity for fair competition while also weeding out pseudo-innovators by encouraging competition, so that the policy benefits could be effectively realized. Furthermore, the *Administrative Measures* can be updated on the basis of the existing systems, taking into account the difficulty, depth, and potential market value of corporate R&D and innovation activities, in order that funding for high-quality innovative outcomes would be increased and substantive firm innovation facilitated. CE

References:

Allen F., Qian J., Qian M. Law, Finance, and Economic Growth in China[J]. Journal of Financial Economics, 2005(1): 57-116.

An T. L., Zhou S. D., Pi J. C. The Stimulating Effects of R&D Subsidies on Independent Innovation of Chinese Enterprises[J]. Economic Research Journal, 2009(10): 87-98+120.

Bloom N., Griffith R., Van Reenen J. Do R&D Tax Credits Work? Evidence from a Panel of Countries 1979-1997[J]. Journal of Public Economics, 2002(1): 1-31.

Bronzini R., Iachini E. Are Incentives for R&D Effective? Evidence from a Regression Discontinuity Approach[J]. American Economic Journal: Economic Policy, 2014(4): 100-134.

Bukht R., Heeks R. Defining, Conceptualising and Measuring the Digital Economy[R]. Development Informatics Working Papers,2017.

Chen D. Q., Qing H. Corporate Governance Research in the Digital Economy: New Paradigms and Frontiers of Practice[J]. Journal of Management World, 2022(6): 97-124.

Chen Q. Y., Lin S. T., Zhang X. The Effect of China's Incentive Policies for Technological Innovation: Incentivizing Quantity or Quality[J]. China Industrial Economics, 2020(4):79-96.

Chen Z., Liu Z., Suárez Serrato J. C., et al. Notching R&D Investment with Corporate Income Tax Cuts in China[J]. American Economic Review, 2021(7): 2065-2100.

Cheng H., Zhong G. Y. Why Is the Performance of R&D Policy Distorted? Evidence from “China Employer-Employee Survey” (CEES)[J]. Social Sciences in Guangdong, 2018(2): 29-39.

Dai X. Y., Cheng L. W. Towards More Effective Industrial Policies: Productivity and Mark-up Analysis of Chinese Manufacturing Firms[J]. The Journal of World Economy, 2019 (3): 69-93.

Demertzis M., Merler S., Wolff G. B. Capital Markets Union and the Fintech Opportunity[J]. Journal of Financial Regulation, 2018(1): 157-165.

Deng D., Pan G. X., Lin X. L. The Impact of Digital Economy Development on Local Fiscal Sustainability in China[J]. Contemporary Finance & Economics, 2021(9): 38-52.

Ding C. M., Wang C., Chen H. Optimize the Doing Business Environment to Promote Balanced Economic Development between North and South: Evolution from Limited Economic Access Order to Open Economic Access Order[J]. Journal of Quantitative & Technological Economics, 2024(1): 110-129.

Dong S. K., Liu X. Z., Li N. Does Enterprise Digital Transformation Reduce Research and Experimental Development Manipulation?[J]. Journal of Quantitative & Technological Economics, 2023(4): 28-51.

Dyck A., Morse A., Zingales L. Who Blows the Whistle on Corporate Fraud?[J]. The Journal of Finance, 2010(6): 2213-2253.

Dyck A., Zingales L. Private Benefits of Control: An International Comparison[J]. The Journal of Finance, 2004(2): 537-600.

Gomber P., Kauffman R. J., Parker C., et al. On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services[J]. Journal of Management Information Systems, 2018(1): 220-265.

Gu Y. Y., Shen K. R. The Effect of Local Governments’ Behavior on Corporate R&D Investment——Empirical Analysis Based on China’s Provincial Panel Data[J]. China Industrial Economics, 2012(10): 77-88.

Guo B. N., Wang Y., Zhang H. Does Digital Economy Improve Urban Air Quality: Quasi Natural Experiment Based on National Big Data Comprehensive Pilot Zone[J]. Journal of Guangdong University of Finance & Economics, 2022(1): 58-74.

Hall B. H., Harhoff D. Recent Research on the Economics of Patents[J]. Annual Review Economics, 2012(1): 541-565.

He F., Liu G. C. Digital Information Dissemination and Corporate Innovation[J]. Journal of Quantitative & Technological Economics, 2022(12): 111-131.

Hong Y. M., Wang S. Y. How Is Big Data Changing Economic Research Paradigms? [J]. Journal of Management World, 2021(10): 40-55+72+56.

Huang Q. H., Yu Y. Z., Zhang S. L. Internet Development and Productivity Growth in Manufacturing Industry: Internal Mechanism and China Experiences[J]. China Industrial Economics, 2019(8): 5-23.

Jiang T. Mediating Effects and Moderating Effects in Causal Inference[J]. China Industrial Economics, 2022(5): 100-120.

Joe J. R., Louis H., Robinson D. Managers’ and Investors’ Responses to Media Exposure of Board Ineffectiveness[J]. Journal of Financial and Quantitative Analysis, 2009(3): 579-605.

Kang Z. Y. Does Chinese Government Subsidies Promote the Quality of Enterprise Patents?[J]. Studies in Science of Science, 2018(1): 69-80.

Lach S. Do R&D Subsidies Stimulate or Displace Private R&D? Evidence from Israel[J]. The Journal of Industrial Economics, 2002(4): 369-390.

Li C. T., Yan X. W., Song M., et al. Fintech and Corporate Innovation——Evidence from Chinese NEEQ-Listed Companies[J]. China Industrial Economics, 2020(1): 81-98.

Li J., Jiang J. O., Chen C. M. Relationship between Digital Financial Inclusion and Corporate Innovation from the Perspective of Inclusion: Evidence Based on Chinese A-share Listed Companies[J]. Journal of Management Science, 2020(6): 16-29.

Li W. F., Du J., Zhang H. Do R&D Subsidies Really Stimulate Firms’ R&D Self-financing Investment: New Evidence from China’s Listed Firms[J]. Journal of Financial Research, 2017(10): 130-145.

Li W. J., Zheng M. N. Is it Substantive Innovation or Strategic Innovation?——Impact of Macroeconomic Policies on Micro-enterprises’ Innovation[J]. Economic Research Journal, 2016(4): 60-73.

Li Y. L. Preferential Tax Policy and Innovation Efficiency of High-tech Industry[J]. Journal of Quantitative & Technological Economics, 2018(1): 60-76.

Li. W. A., Li H. B., Li C. H. Innovation Incentives or Tax Shield?—A Study of the Tax Preferences of High-tech Firms[J]. Science Research Management, 2016(11): 61-70.

Lin Y. F. Industrial Policy and China's Economic Development: From the Perspective of New Structural Economics[J]. Fudan Journal (Social Sciences Edition), 2017(2): 148-153.

Liu D. Y., Chen T., Liu X. Y., et al. Do More Subsidies Promote Greater Innovation? Evidence from the Chinese Electronic Manufacturing Industry[J]. Economic Modelling, 2019(8): 441-452.

Liu M. T., Fang X. B., Li G. Q. Government's Digital Concern and Enterprise's Digital Innovation: Evidence from Text Analysis of Government Work Report[J]. Journal of China Economics, 2023(7): 111-142.

Liu Q. The Rule-of-Law Logic of Inclusive and Prudential Regulation from the Perspective of the Digital Economy[J]. Chinese Journal of Law, 2022(4): 37-51.

Lu G. Q., Wang Z., Zhang C. Y. Research on the Performance of Subsidizing Innovation for Chinese Strategic Emerging Industry[J]. Economic Research Journal, 2014(7): 44-55.

Mao Q. L., Xu J. Y. The Effect of Government Subsidy on Firms' New Product Innovation——An Analysis Based on the Moderate Interval of Subsidy Intensity[J]. China Industrial Economics, 2015(6): 94-107.

Nie A. Y., Pan X. H. Enhancing Local Government Governance with the Digital Economy: An Empirical Examination Using Panel Data from 275 Chinese Cities (2011-2019)[J]. Comparative Economic & Social Systems, 2023(6): 109-120.

Qiu Y. D. How Does Selective Industrial Policy Affect Business Performance? Empirical Evidence from the Qualification of High-tech firms[J]. Journal of Guangdong University of Finance & Economics, 2020(3): 70-83.

Qiu Z. X., Zhou Y. H. Development of Digital Economy and Regional Total Factor Productivity: An Analysis Based on National Big Data Comprehensive Pilot Zone[J]. Journal of Finance and Economics, 2021(7): 4-17.

Ren B. P., He H. C. Construction of China's Digital Economy Innovation System in the New Journey of Chinese Modernization[J]. Shanghai Journal of Economics, 2022(12): 17-26.

Shang H. T., Fang D. Government Subsidies, Risk-Taking and Technological Innovation of Private Science and Technology Enterprises[J]. Journal of Management, 2021(6): 45-62.

Shen H. B., Kou H., Zhang C. An Empirical Study of Financial Development, Financing Constraints and Corporate Investment[J]. China Industrial Economics, 2010(6): 55-64.

Stiglitz J. E., Lin J. Y., Monga C. The Rejuvenation of Industrial Policy[R]. World Bank Policy Research Working Paper Series, 2013.

Sun W. Z., Mao N., Lan F., et al. Policy Empowerment, Digital Ecosystem and Enterprise Digital Transformation: A Quasi Natural Experiment Based on the National Big Data Comprehensive Experimental Zone[J]. China Industrial Economics, 2023(9): 117-135.

Sun Z. Y., Zhou Y. Q., Zhang Y. Competitive or Pervasive? Government Incentive Policy and the Restraining Effect of Enterprise's Innovation Tendency[J]. Accounting Research, 2021(7): 99-112.

Tang S., Wu X. C., Zhu J. Digital Finance and Enterprise Technology Innovation: Structural Feature, Mechanism Identification and Effect Difference under Financial Supervision[J]. Journal of Management World, 2020(5): 52-66+9.

Tang W., Cai W. J., Cui Y. G. Integrity Culture and Corporate Innovation[J]. Science Research Management, 2020(4): 11-22.

Tong T. W., He W., He Z. L., et al. Patent Regime Shift and Firm Innovation: Evidence from the Second Amendment to China's Patent Law[J]. Academy of Management Annual Meeting Proceedings, 2014(1): 14174.

Wan J. Y., Zhou Q., Xiao Y. Digital Finance, Financial Constraint and Enterprise Innovation[J]. Economic Review, 2020(1): 71-83.

Wan Y. X., Xu Y. B., Xu W. H. Additional Deduction Policy, R&D Manipulation and Independent Innovation of Private Firms[J]. Science Research Management, 2020(2): 83-93.

Wang F. S., Wang Y., Liu S. Y. Research on the Influence of Online Media Reports on Earnings Management Based on the Perspective on Abnormal Investor Attention[J]. Nankai Business Review, 2021(5): 116-129.

Wang K., Zhang X. The Effect of Media Coverage on Disciplining Firms' Pollution Behaviors: Evidence from Chinese Heavy Polluting Listed Companies[J]. Journal of Cleaner Production, 2021(1): 123035.

Wang Y., Stuart T., Li J. Fraud and Innovation[J]. Administrative Science Quarterly, 2021(2): 267-297.

Wu J., Wu T. Fiscal Transparency, Local Government Governance Capacity and Regional Innovation[J]. Statistics & Decision, 2022(15): 149-153.

Wu W. W., Zhang T. Y. The Asymmetric Influence of Non-R&D Subsidies and R&D Subsidies on Innovation Output of New Ventures[J]. Journal of Management World, 2021(3): 137-160+10.

Wu W. Y., Tang S. F., Wei S. W. Social Responsibility, Media Attention and Corporate Financial Risk: Based on Empirical Evidence of Chinese Listed Companies[J]. Journal of Management, 2022(1): 124-141.

Xia H. X., Tan Q. M., Bai J. H. Business Environment, Enterprise Rent-seeking and Market Innovation: Evidence from the China Enterprise Survey[J]. Economic Research Journal, 2019(4): 84-98.

Xia Q. H., Huang J. The Influence of Government Resource Allocation on the Relationship between Market Competition and Corporate Innovation Investment: Evidence of High-tech firms in China[J]. Business and Management Journal, 2019(8): 5-20.

Xie W. D. “New Infrastructure Construction” and Urban Innovation: A Quasi-Natural Experiment Based on the “Broadband China” Strategy[J]. Economic Review, 2022(5): 18-34.

Xie X. L., Shen Y., Zhang H. X., et al. Can Digital Finance Promote Entrepreneurship?——Evidence from China[J]. China Economic Quarterly, 2018(4): 1557-1580.

Xu W., Chen D. H. Information Effect of “We Media” Disclosure: Evidence from Sina Weibo[J]. Journal of Financial Research, 2016(3): 157-173.

Yang G. C., Liu J., Lian P., et al. Tax-reducing Incentives, R&D Manipulation and R&D Performance[J]. Economic Research Journal, 2017(8): 110-124.

Yang G. C., Rui M. The Incentive Effect and Catering Effect of Tax-reducing Policy for High-tech Firms[J]. Economic Research Journal, 2020(9): 174-191.

Yang G. C., Zhang L. N. How to Make Industrial Policy More Effective?——Evidence Based on Massive Media Data and R&D Manipulation[J]. China Economic Quarterly, 2021(6): 2173-2194.

Yang R. L., Hou F. Y. The Efficient Boundary of Industrial Policy: An Incomplete Contract Perspective[J]. Journal of Management World, 2019(10): 82-94+219-220.

Ye G. L., Cheng L., Zhang H. Impacts of Strengthening Competition Policy and Industrial Policy Transformation on Market Efficiency——The Analysis of the Efficient Market and Effective Government[J]. China Industrial Economics, 2022(1): 74-92.

Ying Q. W., He S. Y. Corporate Innovation Strategies under the Government’s R&D Subsidies: “Making up the Number” or “Strive for Excellence”?[J]. Nankai Business Review, 2022(2): 57-69.

You J. X., Zhang B. H., Zhang L. Who Captures the Power of the Pen?[J]. The Review of Financial Studies, 2018(1): 43-96.

Yu G. M., Fan R., Zhong H. J. Chinese Industrial Policy and Corporate Technological Innovation[J]. China Industrial Economics, 2016(12): 5-22.

Yu W., Wang M. J., Jin X. R. Political Connection and Financing Constraints: Information Effect and Resource Effect[J]. Economic Research Journal, 2012 (9): 125-139.

Zhang H. Y., Wu Z. L. How High-tech Enterprise Recognition Affects Enterprise Innovation Behavior Empirical Evidence from Fuzzy Regression Discontinuity[J]. Business and Management Journal, 2022(6): 63-81.

Zhang J., Gao D. B., Xia Y. L. Do Patents Drive Economic Growth in China——An Explanation Based on Government Patent Subsidy Policy[J]. China Industrial Economics, 2016(1): 83-98.

Zhang J., Zheng W. P. Has Catch-up Strategy of Innovation Inhibited the Quality of China’s Patents? [J]. Economic Research Journal, 2018(5): 28-41.

Zhang W. K. The Endogenous Attributes and Industrial Organization of Digital Economy[J]. Journal of Management World, 2022(7): 79-90.

Zhang Y., Cheng Y., She G. M. Can Government Subsidy Improve High-tech Firms’ Independent Innovation? Evidence from Zhongguancun Firm Panel Data[J]. Journal of Financial Research, 2018(10): 123-140.

Zhang Z. Y., Yang D., Yang B. Q. A Research into Expense Manipulation Behaviors in the Cognizance of High-tech Companies[J]. Nankai Business Review, 2019(5): 155-164.

Zhang Z. Y., Zhao J. An Analysis and Comment on the Effect of Implementing Industrial Policy[J]. China Business and Market, 2008(7): 28-30.

Zhao T., Zhang Z., Liang S. K. Digital Economy, Entrepreneurship, and High-Quality Economic Development: Empirical Evidence from Urban China[J]. Journal of Management World, 2020(10): 65-76.

Zhou H. T., Lin Y. H. Research on the Construction of Market-Oriented Policy of Government Support for Scientific and Technological Innovation of Enterprises: Base on the Theoretical Framework of Market Demand-Capacity Supply-Environment System[J]. Science of Science and Management of S.& T., 2016(5): 3-16.

Zhou Z. J., Wang S., Zhang Y. Intellectual Property Protection and Information Dilemma of Enterprise Innovation[J]. China Industrial Economics, 2022(6): 136-154.

Zhuang Q. Q., Lin R. X., Luo W. J. Tolerance for Failure and Enterprise Innovation: Evidence from the Reform of State-Owned Enterprises[J]. Business and Management Journal, 2022(4): 23-44.