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Nonlinear Impact of the Digital Inclusive Finance on Enterprise Technological Innovation Based on the AK Model and PSTR Empirical Analysis

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ABSTRACT

Using a panel smooth conversion model, data of listed companies in the Chinese A-stock market and the digital inclusive finance index from 2011 to 2018 are used to empirically test the nonlinear impact and heterogeneity of digital inclusive finance on corporate technological innovation. The results show the following: First, the development of digital inclusive finance has a nonlinear effect of first promoting and then inhibiting the technological innovation of enterprises. Second, the nonlinear impact of digital inclusive finance development on the technological innovation of SMEs is more obvious. Finally, in the subdivision dimension of digital inclusive finance, the depth of use has a significant positive effect on the technological innovation of enterprises, the breadth of coverage has a significant inhibitory effect on the impact of enterprise innovation, and the degree of digitization is realized as an inverted U-shaped relationship that first rises and then falls.

KEYWORDS

Digital Inclusive Finance, Panel Smooth Transition Model, Technological Innovation

1. INTRODUCTION

Since the outbreak of COVID-19, the world economy has been severely affected, and the global industrial pattern has undergone new changes. In the context of the impact of the epidemic on the economy, the Chinese REPORT ON THE WORK OF THE GOVERNMENT in 2022 proposed promoting technological innovation, industrial optimization and industrial upgrading to deeply implement the innovation-driven development strategy and consolidate the foundation of the real economy (Tay, 2022). Technological innovation has become the theme of the times and will also become a major direction for China's future development. As the main part of China is embarking on

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building an innovative country, the level of technological innovation of enterprises will also directly affect the quality of economic development (Acemoglu, 2018). However, due to the long-standing financial exclusion in the traditional financial field, many SMEs with relatively high credit risks and limited mortgage guarantees are subject to strong financing constraints when engaging in high-risk, high-investment innovative activities (Feng, 2022).

In recent years, with the vigorous development of digital inclusive finance, the problems of difficult and expensive financing encountered by enterprises in the process of R&D innovation have been alleviated to a certain extent (Kapoor, 2014; Laeven, 2015). Under this support, the main role of enterprises in innovation has been strengthened. However, as an emerging financial innovation model, the existing regulatory mechanisms and legal provisions on digital inclusive finance are not perfect, and when the lack of supervision of digital inclusive finance develops to a certain level, it will inevitably lead to the phenomenon of idling and arbitrage of funds, which will breed credit risks and then inhibit the flow of funds to the real economy. Except for a small portion of large enterprises, it is difficult for most enterprises to carry out innovation activities and to obtain innovation funds only through internal financing (Yu, 2021), and when digital inclusive finance develops markedly, R&D companies that rely heavily on external financing may face the same financing difficulties as the difficulties faced in the traditional financial era, which inhibits the improvement of their innovation capabilities. Thus, can vigorously developing digital inclusive finance have a lasting positive impact on corporate technological innovation? Will the extreme development of digital finance inhibit the innovation capability of enterprises? These are such questions that need to be clarified in this paper.

We contribute to the literature in the following ways. First, based on the revised AK model and the Schumpeter multisector endogenous growth model, a mathematical model is constructed to explore the nonlinear impact mechanism of digital inclusive finance on enterprise technological innovation. Second, based on the panel smooth transition model (PSTR), this paper empirically tests the nonlinear continuous change in the development of digital inclusive finance with respect to the technological innovation of enterprises and provides a theoretical basis for the formulation of digital inclusive finance policies.

2. LITERATURE REVIEW

When companies carry out innovation activities, they need a lot of money for R&D, training, purchasing capital equipment, marketing new products and processes, etc. (Hall, 2010). However, the rewards of innovation are long and uncertain. Therefore, when companies carry out innovation activities with high technical and market risks, they are often reluctant to publish information about innovation projects out of fear of losing their competitive advantage and preventing competitors from imitating (Carreira, 2010). Conversely, due to high risk and information asymmetry, banks and other financial intermediaries incur high established costs in collecting corporate information (Hall, 2010), making it difficult to assess the quality of these innovative activities. Therefore, they are reluctant to provide innovation investment or loans for enterprises (Laursen, 2005), and the lack of funds seriously restricts the innovation activities of enterprises. Existing studies have demonstrated from empirical and theoretical perspectives that digital inclusive finance can reduce corporate financing costs (He, 2022), improve production and operation efficiency (Lo et al., 2011), ease credit restrictions on capital flows to its most productive projects (Amore, 2013) and promote technological innovation-driven growth. Therefore, digital inclusive finance plays a crucial role in promoting corporate innovation, and as a financial innovation model, it will inevitably have an important impact on corporate innovation.

Digital inclusive finance opens a new form of finance that uses digital technology to drive the growth of financial inclusion, and it is an extension and deepening of financial development. On the one hand, digital inclusive finance has greater breadth and depth compared with digital finance, and can deeply expand the scope and reach of financial services, promote the growth of financial inclusion, and realize the deepening of the scale of financial development (Liu, 2021). On the other hand, compared with inclusive finance, the deep integration of digital inclusive finance with the internet, as well as big data, cloud computing, artificial intelligence and other information technologies, provides the market with low-cost, convenient and informational financial services that are difficult to achieve with traditional finance (Cao, 2021). The increased level of digitization in digital inclusive finance has greatly improved financial efficiency.

Although digital finance is the product of the deep integration of digital technology and financial innovation, "finance is the essence, technology is the means", it has not changed its own financial logic, nor has it changed the basic core of the financial industry's "risk-return-trade-off". Therefore, research on digital finance can still be incorporated into the framework of financial development theory. Based on the view that there is a complementary relationship between digital inclusive finance and traditional finance (Wang, 2021), the development of digital inclusive finance is similar to financial development, and there is a "possibility frontier", which may have a nonlinear relationship in its impact on corporate innovation.

When digital inclusive finance is lower than a certain scale, its expansion usually has a positive effect on technological innovation. The development of digital inclusive finance compensates for the insufficient supply of traditional finance and greatly improves inclusion by providing convenient services and low barriers to entry (Cao, 2021; Berg, 2020), expanding the service boundaries of traditional finance, alleviating information asymmetry (Demertzis, 2017; Chen, 2021), controlling financing costs and reducing corporate risks (Li, 2020), facilitating the conduct of innovative R&D activities (Wu, 2022) and significantly promoting the innovation and development of companies. According to the relationship between financial scale development and R&D innovation, Maskus (2012) pointed out that the expansion of the private credit market can help alleviate financing constraints and stimulate R&D expenditures. Jiang (2021) uses financial scale (financial correlation ratio) to measure the development level of financial intermediary organizations, and empirical evidence shows that there is a positive relationship between financial intermediaries and technological innovation. Nanda (2014) and Ramana and Tom Nicholas (2014) studied bank distress and the level and quality of innovation of companies during the Great Depression and empirically found that the impact of insufficient credit in financial institutions on credit availability will limit resource allocation and inhibit corporate-level investment, thereby negatively affecting corporate innovation.

With the introduction of concepts such as the "financial possibility frontier" (Guo, 2020; Arcand, 2012; Cecchetti & Kharroubi, 2012; Siong H L, 2014; Thorsten B, 2014), the nonlinear characteristics of financial overexpansion affecting technological innovation have been supported by increasing empirical evidence. It is believed that there should be a reasonable limit for financial scale, and excessive expansion will have a negative marginal effect on economic innovation (Nie, 2022; Yang, 2022). Li (2017) uses the loan balance of the formal financial sector/GDP to measure the financial scale and empirically finds that there is an asymmetric relationship between financial development and technological progress. When the difference between the growth rate of financial development and the economic growth rate of the real sector exceeds the critical value, the effect of financial development on technological progress will change from promoting to inhibiting innovation. Law (2018) selects two financial deepening indicators of private sector credit and domestic credit to measure the level of financial development, uses the generalized method of moments estimation (GMM) to analyze the nonlinear relationship between financial development and innovation, and finds a nonlinear relationship. Zhang (2021) found that the continuous expansion of the financial industry has a stable inverted U-shaped relationship with the innovation investment of local enterprises, which reveals the double impact of China's financial scale on enterprise innovation activities. In terms of expanding to digital inclusive finance, Tang (2020) found that the excessive development of scale has no obvious impact on the improvement of the innovation efficiency of enterprises after lagging the indicators of the breadth of digital inclusive finance. In addition, although the excessive use of digital technology in the financial field has promoted the innovation of financial intermediaries, it has weakened the motivation of financial institutions to screen and monitor borrowing companies, exacerbated the mismatch of credit supply, and hindered corporate innovation and R&D.

The reason why the excessive development of financial scale can cause negative asymmetric effects can be summarized in two ways as to its inhibitory effect on innovation. First, although digital inclusive finance has promoted the reform of financial structure and the improvement of financial efficiency, excessive financial activities may misallocate resources, leading to the withdrawal of physical capital from the production sector and instead the flow of such capital to nonphysical sectors such as financial institutions (Tori, 2017). Second, when the financial sector expands, high-quality and innovative talent will be attracted to the financial sector through high salaries (Axelson, 2015), resulting in insufficient allocation of human resources in the R&D and innovation sector, which ultimately damages the development of real industries and technological innovation.

3. MATHEMATICAL MODEL CONSTRUCTION OF THE IMPACT OF DIGITAL FINANCE ON ENTERPRISE INNOVATION CAPABILITY

Due to the existence of financial friction, the development of digital finance may affect the technological innovation of enterprises by affecting financing constraints (Nikolov, 2021). Taking financial friction as a bridge, this paper comprehensively constructs two models for mathematical analysis, which mainly refer to the multisector endogenous growth theoretical model framework used by Acemoglu (2006) and Laeven (2015).

3.1. General Products Sector

The general product sector combines N kinds of industry final products to produce general products, assumes that the market is perfectly competitive and combines various general products with fixed substitution elastic production functions. Y_i is the specific general product industry, Y_t is the generic product produced at period *t*, ϕ_i is the importance of the products produced by industry i, and ε describes the substitution effect between final products (assuming that all products can replace each other, then $\varepsilon \geq 1$).

$$Y_t = \left(\sum_{i=1}^{n} \varnothing_i Y_{it}^{\frac{e}{e-1}} \right)^{\frac{e}{e-1}} \tag{1}$$

In this model, each general product sector pursues the maximum profit by choosing the optimal industry final product input mix $\left\{ Y_{1t}, Y_{2t} \ldots Y_{nt} \right\}$ under the condition that the final product and the general product price are fixed.

3.2. Final Product Sector

The final sector uses intermediate products to produce and obtain final products, which we express with a production function that includes technology, labor, and intermediate inputs. Y_{it} is the final finished product of industry *i*, used for consumption, as an input for corporate and financial innovation, and for the production of intermediate goods. L is the labor supply, and the labor endowment is equal to the sum of the labor input in each sector. *j* is the required quantity of intermediates. A_{it} represents the production efficiency of industry *i* in period *t*, reflecting its technical level, and $\boldsymbol{\alpha}$ represents the degree of input of intermediate products.

$$Y_{it} = L_{it}^{1-\alpha} \int_0^1 A_{it}\left(j\right)^{1-\alpha} x_{it}\left(j\right)^{\alpha} d_j \tag{2}$$

The production of the final product is carried out under perfect competition, so the price of each intermediate product is equal to its marginal product. In this model, each final product sector pursues the maximum profit by choosing to change the input degree and labor amount of the intermediate factor under the condition that the cost (nominal wage level W) of the intermediate factor and labor factor is determined, so the optimization function is as follows:

$$\max_{x_{it}\left(j\right),L_{it}} P_{it} Y_{it} - W_t L_{it} - \int_0^1 P_{it} x_{it}\left(j\right)^{\alpha} d_j = P_{it} L_{it}^{1-\alpha} \int_0^1 A_{it}\left(j\right)^{1-\alpha} x_{it}\left(j\right)^{\alpha} d_j - W_t L_{it} - \int_0^1 P_{it}\left(j\right) x_{it}\left(j\right)^{\alpha} d_j \tag{3}$$

For intermediate product j,

$$P_{it}\left(j\right) = P_{it} \frac{\partial Y_{it}}{\partial x_{it}\left(j\right)} = P_{it} L_{it}^{1-\alpha} \alpha A_{it}\left(j\right)^{1-\alpha} x_{it}\left(j\right)^{\alpha-1} \tag{4}$$

$$W_t\left(j\right) = P_{it} \frac{\partial Y_{it}}{\partial L_{it}} = \left(1-\alpha\right) P_{it} L_{it}^{-\alpha} \int_0^1 A_{it}\left(j\right)^{1-\alpha} x_{it}\left(j\right)^{\alpha} d_j \tag{5}$$

Under the condition that the intermediate product sector of each industry pursues profit maximization, the optimal intermediate product input can be selected as follows:

$$\max_{x_{it}\left(j\right)} P_{it}\left(j\right) x_{it}\left(j\right) - P_{it} x_{it}\left(j\right) = P_{it} L_{it}^{1-\alpha} \alpha A_{it}\left(j\right)^{1-\alpha} x_{it}\left(j\right)^{\alpha} - P_{it} x_{it}\left(j\right) \tag{6}$$

The optimal output of the intermediate goods sector can be obtained as follows:

$$x_{it}^{*}\left(j\right) = \alpha^{2/\left(1-\alpha\right)} L_{it} A_{it}\left(j\right) \tag{7}$$

Substitute it into the profit function to obtain the optimal profit as follows:

$$\pi_{it}^{*}\left(j\right) = \left(1-\alpha\right) \alpha^{\left(1+\alpha\right)/\left(1-\alpha\right)} P_{it} L_{it} A_{it}\left(j\right) \tag{8}$$

The corresponding optimal output expression at this time is:

$$Y_{it}^{*} = \alpha^{2\alpha/\left(1-\alpha\right)} L_{it} A_{it} \tag{9}$$

3.3. Intermediate Product Sector

In each intermediate product production sector i, the entrepreneur puts forward the idea of upgrading in period t-1, hoping that the innovation can successfully iterate the product and obtain monopoly profit. However, in period t, these ideas have some probability of failure. Assuming that the probability of success is μ, if the innovation of R&D activities is successful, the production efficiency A_t becomes δ times the previous period (δ ³1); if it fails, the production efficiency of the new period will be the same as the previous period.

$$A_{it} j = \begin{cases} \delta_i A_{it-1}\left(j\right), & PROB\ \mu_{it}\left(j\right) \\ A_{it-1}\left(j\right), & PROB\ 1-\mu_{it}\left(j\right) \end{cases} \tag{10}$$

For the intermediate product sector, A_{it} and δ can be changed by increasing R&D input. In the research of Aghion and Howitt, the R&D production function of the intermediate product production sector *i* is set as follows:

$$\mu_{it}\left(j\right) = \eta\left(\frac{R_{it}\left(j\right)}{A_{it}^{*}\left(j\right)}\right) = \lambda_i\left(\frac{R_{it}\left(j\right)}{A_{it}^{*}\left(j\right)}\right)^{0.5} \tag{11}$$

where $R_{it}\left(j\right)$ is the R&D investment; λ_i is the R&D efficiency parameter; and $A_{it}^{*}\left(j\right)$ is the innovation target.

However, the setting of this function does not take the effect of scale effects into account. In reality, economic growth will increase with population growth, so the market size of successful innovative companies will expand further with population growth. In addition, the expansion of the population also increases the number of potential R&D scientists, which will also increase the probability of successful innovation. However, Jones found that since 1953, the number of R&D-related scientific researchers has increased by 9 times, but the efficiency of the production sector has not shown a significant growth trend, indicating that the scale effect of the R&D function response is inconsistent with the actual law.

Based on this, taking the avoidance of scale effects in the R&D process into account, the probability of innovation success is expressed by the improved R&D production function:

$$\mu_{it}\left(j\right) = \eta\left(\frac{R_{it}\left(j\right)}{L_{it}A_{it}^{*}\left(j\right)}\right) = \lambda_i\left(\frac{R_{it}\left(j\right)}{L_{it}A_{it}^{*}\left(j\right)}\right)^{0.5} \tag{12}$$

Among them, A is the R&D investment, B is the R&D efficiency parameter, and C is the innovation target.

3.4. Financial Sector

Enterprise R&D activities have the characteristics of high risk, long cycle and large investment, and enterprises need external financing to meet capital needs (Guo, 2020). Due to the existence of information asymmetry, to avoid adverse selection and moral hazard problems, financial institutions must pay a certain cost for information collection, due diligence and investment evaluation when selecting projects (Luo, 2022). Rajan (1998) pointed out that with the development of finance, the external financing cost of enterprises will decrease. At the same time, due to the large differences in the risks of different investment projects, there is a large gap between evaluation projects and costs in different industries (Gong, 2014), which leads to the industry structure characteristics in financial development. Based on Schumpeter's theory of endogenous growth, this paper characterizes the financial sector with reference to the research of Yi (2015).

Assuming that the probability of a firm's R&D earning a positive return **is θ**, if the return earned by a successful institution is P_{it}^{*}, then the marginal benefit of the financial sector is $, P_{it}^{*}$. f_{it} is the friction coefficient, reflecting the degree of financial friction. The cost of financing in the financial sector is set as $f_{it}P_{it}R_{it}\left(j\right)$, which is used for the selection of ex ante projects and the supervision of the financial sector ex post, as well as some capital leakage. In perfect competition, the marginal cost of the institution is equal to the marginal revenue, so it can be known that:

$$\theta P_{it}^{*} - f_{it}P_{it}R_{it}\left(j\right) = 0 \tag{13}$$

The expected return to the financial sector from the intermediate goods sector is as follows:

$$P_{it}^{*} = \frac{f_{it}R_{it}\left(j\right)}{\theta}P_{it} \tag{14}$$

3.5. Model Solving

Manufacturers in the intermediate product sector enter freely, their main input is the final product of the industry, and the intermediate product produced is then put into the final production sector to produce the final product. To obtain monopoly profits, intermediate product manufacturers will improve the production technology of intermediate products by increasing R&D input. If the innovation of the middle sector is successful, technological progress will produce new products, and the enterprise will obtain a short-term monopoly profit.

However, due to the rapid product iteration speed, old products are constantly eliminated by new products, and the monopoly profit of innovation will have a time limit. Only by continuously investing in R&D and continuously providing innovative impetus to carry out innovation activities, can intermediate product manufacturers obtain sustainable monopoly profits (Zheng, 2011). In the "creative destruction" multisector endogenous growth model, we focus on analyzing the optimal behavior of intermediary firms under constraints to study the impact of financial frictions on innovation activities.

When establishing the model of the middleman, the function of changing the R&D production function from the optimal input to the innovation probability is as follows:

$$R_{it}\left(j\right) = \left(\frac{\mu_{it}\left(j\right)}{\lambda_{i}}\right)^{2} L_{it}A_{it}^{*}\left(j\right) \tag{15}$$

When there is no financial friction, there is no additional cost in the middle sector and no loss of funds in the process of R&D innovation. At this time, to explore the optimal behavior of the middle sector, the innovation probability optimization problem can be transformed into an input quantity optimization problem under conditional constraints.

The innovation income of the middle sector depends on whether the innovation is successful or not. If the innovation is successful, the income $\grave{A}_{it}j$ will be obtained. If it fails, no additional profit will be obtained, that is, the income will be 0. According to this, it can be calculated that the expectation of innovation benefit is $¼_{it}jÀ_{it}j$, and the cost of innovation activities is $P_{it}R_{it}j$. Then, the problem is an unconstrained optimization problem as follows:

$$\max_{\mu_{it}(j)} \mu_{it}(j)\pi_{it}(j) - P_{it}R_{it}(j) = (1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}\mu_{it}(j)P_{it}L_{it}A_{it}^{*}(j) - P_{it}\left(\frac{\mu_{it}(j)}{\lambda_i}\right)^2 L_{it}A_{it}^{*}j \tag{16}$$

The result is as follows:

$$¼_{it}(j) = \frac{»_i^2}{2}(1-±)±^{\frac{1+±}{1-±}} \tag{17}$$

From this result, it can be seen that the innovation success probability of intermediate product j is related to the R&D efficiency of industry i and the investment degree of intermediate products, so the innovation probability of all intermediate products in industry i is equal, as follows:

$$\mu_{it} = \mu_{it}(j) = \frac{\lambda_i^2}{2}(1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}} \tag{18}$$

When there is a certain financial friction (0<f<+¥), if the intermediate product sector wants to improve its efficiency and obtain a monopoly profit, it needs to pay a certain cost to the financial institution for financing. The optimal cost of financing the intermediate product sector is as follows:

$$P_{it}^{*} = \frac{f_{it}R_{it}(j)}{\theta}P_{it} \tag{19}$$

Then, the optimization problem becomes as follows:

$$\max_{\mu_{it}(j)} \mu_{it}(j)\pi_{it}(j) - P_{it}R_{it}(j) - \frac{f_{it}R_{it}(j)}{\theta}P_{it} = (1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}\mu_{it}(j)P_{it}L_{it}A_{it}^{*}(j) - P_{it}\left(\frac{\mu_{it}(j)}{\lambda_i}\right)^2 L_{it}A_{it}^{*}(j) - \frac{f_{it}R_{it}(j)}{\theta}P_{it} \tag{20}$$

The result is as follows:

$$\mu_{it}(j) = \frac{\theta\lambda_i^2}{2(\theta+f_{it})}(1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}} \tag{21}$$

and there are:

$$\frac{\partial\mu_{it}(j)}{\partial f_{it}} = -\frac{\theta\lambda_i^2}{2(\theta+f_{it})^2}(1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}} < 0 \tag{22}$$

Therefore, the optimal innovation probability is negatively correlated with the financial friction coefficient. With the increase in financial friction, the innovation probability of enterprises will decrease, and the existence of financial friction has a negative impact on the innovation activities of enterprises.

When the financial friction approaches infinity, the financing cost obtained by the intermediate product sector will approach infinity, the income obtained will be negative infinity, and enterprises will have no motivation to innovate.

In summary, the existence of financial frictions has a negative impact on the innovation activities of enterprises, and with the growth of financial scale, financial frictions will decrease first and then increase. Through the derivation of mathematical models, it is proven that with the development of digital inclusive finance, the resulting financial frictions show a trend of decreasing first and then increasing. Financial friction affects the technological innovation of enterprises through financing constraints, so the development of digital finance has a nonlinear impact on enterprise innovation activities, which is manifested in an "inverted U"-shaped relationship that promotes first and then inhibits.

4. EMPIRICAL ANALYSIS OF THE IMPACT OF DIGITAL INCLUSIVE FINANCE ON ENTERPRISE TECHNOLOGICAL INNOVATION

4.1. Panel Smooth Transition Regression Model

The traditional panel regression model believes that the cross-section coefficients of the model are the same, but this setting cannot reflect the relationship between the independent variable and the dependent variable when the sample size is large enough. Therefore, Hansen (1999) proposed a panel threshold regression model:

$$y_{it} = \alpha_{it} + \beta_0 x_{it} I\left(q_{it} \leq c\right) + \beta_1 z_{it} I\left(q_{it} > c\right) + \varepsilon_{it} \tag{23}$$

To distinguish different cross-section coefficients of the model, the model introduces an indicator function and divides different cross-sections into different zones. A mutation occurs when the model variable crosses a threshold, which is estimated by two linear models on either side of the threshold. The model has a premise: the threshold transition mutation exists at a discrete point. However, in reality, zone conversion is a gradual process. Based on the PTR model, Gonzalez (2005) further proposes the nonlinear panel smooth transition regression model (PSTR). Compared with the original model, this model introduces a continuously changing indicative function so that the conversion of the zoning system becomes a continuous and smooth process, which better reflects the real economic and social situation, and the model is superior.

4.1.1. Generalized PSTR Model

In a general sense, the panel smooth transition model (PSTR) is also known as a multisystem model, and the threshold variables and the threshold values of the variables can be set arbitrarily.

$$y_{it} = \alpha_{it} + \beta_0 x_{it} + \sum\nolimits_j^r \beta_j x_{it} I\left(q_{it}^j; \gamma\right) + \varepsilon_{it} \tag{24}$$

where i is the independent variable, t is the time, and j is the threshold variable. In the generalized panel smooth transition regression model, r thresholds are allowed, corresponding to r+1 divisions. When r=1 and m=1, the generalized model degenerates into a two-system model.

4.1.2. Single Threshold Model

The single-threshold model is the two-system model, which has a threshold variable with a unique threshold value, and the model is divided into two regional systems.

$$y_{it} = \alpha_{it} + \beta_1 z_{it} I\left(q_{it} \le \gamma\right) + \beta_2 z_{it} I\left(q_{it} > \gamma\right) + \beta_i x_{it} + \varepsilon_{it} \tag{25}$$

where y_{it} is the explained variable, x_{it} is the explanatory variable, z_{it} is the variable affected by the threshold variable, β_i is the coefficient of the corresponding item, γ is the value of a specific threshold, I is the threshold indicator function, q_{it} is the threshold variable, α_{it} is the individual effect of the company, and ε_{it} is the random fluctuation term, which follows a normal distribution.

4.1.3. Double Threshold Model

The double-threshold model is the three-zone model. The threshold variable of this model has two threshold values, and the model is divided into three intervals.

$$y_{it} = \alpha_{it} + \beta_1 z_{it} I\left(q_{it} \le \gamma_1\right) + \beta_2 z_{it} I\left(\gamma_1 < q_{it} \le \gamma_2\right) + \beta_3 z_{it} I\left(q_{it} > \gamma_2\right) + \beta_i x_{it} + \varepsilon_{it} \tag{26}$$

4.1.4. Transformation Mechanism of the PSTR Model

The panel smooth threshold regression model is a fixed effect model with exogenous explanatory variables, and its basic form is as follows:

$$y_{it} = \alpha_{it} + \beta_0^{'} x_{it} + \sum\nolimits_{j=1}^{r} \beta_1^{'} x_{it} I\left(q_{it}^{j}; \gamma_j, c^j\right) + \varepsilon_{it} \tag{27}$$

where y_{it} is the explained variable, x_{it} is a vector composed of k exogenous explanatory variables, α_i is the fixed individual influence, ε_{it} is the random disturbance term, and the conversion function $g\left(q_{it}^{j}; \gamma_j, c^j\right)$ is the continuous bounded function of q_{it}, which is set to logistic form:

$$g\left(q_{it}^{j}; \gamma_j, c^j\right) = \left\{1 + \exp\left[-\gamma_j \prod\nolimits_{j=1}^{m} \left(q_{it} - c^j\right)\right]\right\}^{-1} \tag{28}$$

where q_{it} is the threshold variable, c^j is the position parameter of the conversion function, and γ_j is the smoothing parameter, that is, the slope of the conversion function. When q_{it} approaches positive infinity, the transfer function $g\left(q_{it}^{j}; \gamma_j, c^j\right)$ approaches 1, and the model belongs to the high regime. When q_{it} approaches negative infinity, the value of the transfer function $g\left(q_{it}^{j}; \gamma_j, c^j\right)$ approaches 0, and the model belongs to the low regime. When the value of the conversion function $g\left(q_{it}^{j}; \gamma_j, c^j\right)$ belongs to (0, 1), the PSTR model can be smoothly transformed from the low regime to the high regime. It is worth noting that when γ approaches 0 or q_{it} is equal to c, $g\left(q_{it}^{j}; \gamma_j, c^j\right)$=0.5, and the PSTR model is a linear fixed effect model. When γ approaches positive infinity, the transfer function will jump around the position parameter, and the PSTR model becomes a general panel threshold model.

According to the basic model of PSTR, we can obtain the influence coefficient as follows:

$$\frac{\partial y_{it}}{\partial q_{it}} = \beta_{01} + \sum_{j=1}^{r} \beta_{11} g\left(q_{it}^{j};\gamma_{j},c^{j}\right) + \sum_{j=1}^{r} \beta_{1}^{'} x_{it} \frac{\partial g\left(q_{it};\gamma_{j},c^{j}\right)}{\partial q_{it}} \tag{29}$$

Among them, the first variable contained in assumption x_{it} is q_{it}.

4.2. Data and Variable Description

Based on the A-share companies in China's Shanghai and Shenzhen stock markets, this paper uses the Peking University Digital Inclusive Finance Index (PKU-DFIIC) (Thorsten B, 2014) to match, constructing panel data from 2011 to 2018. The enterprise data are processed as follows: first, remove the real estate and financial enterprises in the sample; second, remove the listed ST and delisted enterprises within the statistical interval; third, remove the IPO companies within the statistical period; fourth, based on the principle of "five-year continuity" (Jorgensen, 2009), discontinuous samples of five-year data are removed to improve data quality; fifth, variables are processed by 1% Winsorize.

Finally, 1428 enterprises were selected to construct 11424 "enterprise-year" observation samples. The enterprise invention patent data come from the China Innovation Patent Research Database (CIRD), the financial data come from the Wind database, and the digital financial index comes from the "Digital Inclusive Finance Index" of Peking University.

4.2.1. Explanatory Variables

The explanatory variable is the Digital Inclusive Finance Index (DIF, provincial level), which is based on the data of Ant Financial by the Digital Finance Research Center of Peking University and is constructed from three dimensions of coverage (Number of third-party payment accounts), depth of use (Actual usage of digital inclusive finance) and digitalization of digital financial services (mobility, benefit, credit, facilitation) (Thorsten B, 2014). To ensure that the index and other index data can be in the same dimension, the ratio of the digital inclusive finance development index and subindex to 100 is used as the original data.

4.2.2. Explained Variables

The explained variable is the technological innovation of the enterprise, and the number of independent invention patents in the patent application of the enterprise is selected as the proxy variable. Most of the literature uses the R&D input of microenterprises as the proxy variable of technological innovation capability, but in reality, the risk degree of enterprise innovation activities is high, the R&D input is high and the output is difficult, so this measurement method may overestimate the technological innovation of enterprises, so the output of enterprise patent innovation may have a better effect in measuring the innovation of enterprises (Jianjun, 2010). The patent data come from the China Innovation Patent Research Database (CIRD). In this paper, the number of invention patents independently applied to by enterprises in each year is taken as the proxy variable. Because there are many years in which the output of enterprises is zero and other enterprises have filed a large number of patents, this paper adds 1 to the number of patents and takes the logarithm to make the data more statistically significant.

4.2.3. Control Variable

(1) Rate of return on net assets: On the one hand, enterprises with higher performance are more capable of participating in innovation activities, and there is a significant positive correlation between the amount of R&D expenditure and the profitability of enterprises. Enterprises with higher profitability have more funds for R&D activities, which in turn affects the innovation

output of enterprises (Rong, 2017). On the other hand, too high a return on investment may also cause enterprises to lose their motivation to participate in innovation activities (Wen, 2022).
(2) Industry characteristics: The patent output of technology-based manufacturing enterprises is obviously higher than that of nontechnology-based enterprises, so industry attributes and industry characteristics have a great influence on innovation performance in the evaluation model of innovation capability based on patent output (Tang, 2022). Different types of industries have different enthusiasm for innovation, and technology-intensive industries are more dependent on innovation in technology and products to improve their competitiveness [37]. At the same time, the performance of innovation is different in different types of enterprises, and the innovation of technology and products can obtain patent output. This paper uses the ratio of noncurrent assets as the proxy variable of industry characteristics.
(3) The scale of total assets: There is an obvious positive correlation between total assets and innovation capability (Song, 2015; Lu, 2018); compared with small enterprises, large enterprises can obtain more innovative resources (Wen, 2022).
(4) Asset-liability ratio: Enterprises with higher asset-liability ratios still invest less in R&D activities, even if they are in good operating conditions. Enterprises are more inclined to retain profits to keep high liquidity for future rainy days. The asset-liability ratio indicates the level of corporate debt. A higher asset-liability ratio can generate higher financial leverage, and enterprises will face greater debt repayment pressure and liquidity risk (Ji, 2022), which will restrict the use of funds and then affect the R&D investment of enterprises (Tang, 2022). Especially when enterprises are facing a financial crisis, they will often reduce their R&D expenditure first (Rong, 2017; Lu, 2018).
(5) Enterprise age: On the one hand, old enterprises have more resources for R&D activities. On the other hand, old firms may also reduce their investment in innovation due to their market forces (Wen, 2022). Meanwhile, theoretical and empirical evidence also shows that when entering new markets, younger firms invest more in R&D than older firms (Wellalage, 2019). Ayyagari et al. (2011) and Gorodnichenko and Schnitzer (2013) also found that compared with old companies, younger companies tend to participate in more product innovation (table 1).

Table 1. Definition of variables

Type	Variable name	Variable symbol	Variable definition
independent variable	Digital inclusive finance	DIF	The total index of Peking University inclusive finance is divided by 100.
Control variable	Enterprise age Rate of Return on Common Stockholders' Equity Asset-liability ratio Non-current assets ratio total assets	Age Roe Lev Fixr Asset	Natural age of enterprise Net profit/owner's equity Liabilities/total assets Non-current assets/total assets Take logarithm of total assets 10.
dependent variable	Number of invention patents	Pat	The number of patents is increased by 1 and then taken as logarithm.

4.3. Empirical Test and Result Analysis

According to Gonzalez et al.'s (2005) research on the PSTR model, before estimation, the model should be tested for cross-section heterogeneity, i.e., "nonlinearity" test. If there is no nonlinear influence, it proves that the linear frame test of the model is more reasonable; if the heterogeneity is obvious, it is more suitable to use the panel smooth transformation model. Second, the parameters are estimated by the least squares method. Finally, it is necessary to test the residual heterogeneity of the model, namely, the "residual nonlinearity" test, to verify whether the nonlinear model has fully described all the regional system changes.

4.3.1. PSTR Model Test

In this paper, the Wald test, F test and LR test are used to test the cross-section heterogeneity and residual heterogeneity of the model. Gonzalez et al. (2005) noted that in practical applications, considering the two cases of m=1 and m=2 is sufficient to describe the common parameter variability. Therefore, this paper only needs to test four groups of parameters (m=1,2; R=1,2), the number of optimal position parameters m and the number of optimal transfer functions r can be determined, and the results are shown in the following table 2.

Table 2. Cross-section Heterogeneity Test of the Panel Smooth Threshold Regression Model

Inspection type	assumed condition	Test statistics	m=1	m=2
Cross-section heterogeneity test	H0:r=0 H1:r^{3}1	LM	85.041*** (0.000)	89.542*** (0.000)
		LMF	12.487*** (0.000)	6.573*** (0.000)
		LRT	85.359*** (0.000)	89.894*** (0.000)
Residual heterogeneity test	H0:r=1 H1:r^{3}2	LM	3.306 (0.770)	10.030 (0.613)
		LMF	0.481 (0.823)	0.730 (0.723)
		LRT	3.306 (0.770)	10.034 (0.613)

Note: P values are in brackets.

According to the analysis of the results in the above table, the number of location parameters, m, is 1 or 2. At the significance level of 1%, the original assumption of "r=0", "the model is linear", is rejected. There is a significant nonlinear relationship between the development of digital inclusive finance and the level of technological innovation. This means that it is reasonable to use the panel smoothing threshold regression (PSTR) model when studying the relationship between the development of digital inclusive finance and the technological innovation of enterprises. In the test of residual heterogeneity, when the number of positional parameters is m = 1 and m = 2, the original assumption of "one transfer function" cannot be rejected by the three tests, which indicates that the optimal number of transfer functions of the model is r=1.

The Akachi information criterion should be used in the next optimal model selection by adding the penalty of model complexity to avoid overfitting. In this paper, two commonly used model selection methods, the Akachi information criterion (AIC) and the Bayesian information criterion (BIC), are adopted.

The Akachi information criterion was first put forward by the Japanese scientist Akachi chi hong, and it is a common standard to evaluate the quality of model fitting. Based on the concept of entropy, it gives a unified standard of statistical complexity and goodness of fit. Generally, the AIC calculation method is:

$$AIC = 2k - 2\ln(L) \qquad (30)$$

k is the number of model parameters, and L is the likelihood function. When selecting the best model from the alternative models, it is generally considered that the smaller the AIC is, the higher the fitting quality of the model.

The difference between multiple models is mainly reflected in their likelihood functions. If the difference in likelihood functions is not obvious, the model complexity should be considered. Generally, a model with fewer parameters is considered to be better. Generally, when the complexity (k value) of the model increases, the likelihood function L also increases, thus reducing the AIC value. However, when the value of k is large, the likelihood function is flatter, which increases the AIC, and the model complexity is too high, resulting in overfitting. Choosing the optimal solution for the model requires the AIC to be as small as possible. AIC should not only improve the fitting degree (maximum likelihood) of the model but also embed the penalty term to reduce the model parameters, which helps reduce the occurrence of overfitting.

The Bayesian criterion was first put forward by Schwarz, and it is also a common method to evaluate models. During model training, increasing the number of parameters increases the complexity of the model, which leads to an increase in the likelihood function, but this situation also increases the possibility of overfitting. To solve this problem, both the Bayesian and Akachi criteria add a penalty item related to the number of parameters, and the penalty effect of BIC is better. In this case, taking the number of samples into account can effectively avoid the high complexity caused by the improvement of model accuracy.

$$BIC = k\ln(n) - 2\ln(L) \tag{31}$$

k is the number of model parameters, n is the number of samples, and L is the likelihood function. The penalty term *kln(n)* can effectively avoid the dimension disaster phenomenon when the dimension is too large and the training sample data are relatively small.

Therefore, under the condition that the number of optimal transfer functions is determined, the AIC and BIC values in two cases are calculated to select the number of optimal position parameters, and the results are as follows (table 3):

Further thinking finds that when m=1, the AIC and BIC values are smaller than those when m=2, so the optimal value of m is 1. In summary, the optimal number of transfer functions in this model is 1, and the optimal number of position parameters is 1.

Table 3. Selection of the number of optimal position parameters in the smooth threshold regression model of the panel

Test statistics	m=1	m=2
AIC	0.527	0.528
BIC	0.536	0.537

4.3.2. Analysis of Model Parameter Estimation Results

When r=1 and m=1, in this paper, the PSTR model is estimated by nonlinear least squares. The results show that the core explanatory variable DIF is significant at a 1% significance level. The influence of inclusive finance on the innovation ability of enterprises is nonlinear, and its threshold value is c=3.8908. When the digital inclusive finance index is lower than 3.8908, the value of the conversion function approaches 0, and the influence coefficient of digital finance on the innovation patent output of enterprises is 1.4510. Every time the digital inclusive finance index increases by 0.1, the innovation patent output increases by 0.145. When the digital inclusive finance index reaches

3.8908, the conversion function value tends to 0.5, and the influence coefficient of digital finance on the innovation patent output of enterprises is 0.686 (1.4510-0.5*1.5289). At this time, for every 0.1 increase in the digital inclusive finance index, the innovation patent output increases by 0.0687. When the digital inclusive finance index is greater than 3.8908, the conversion function value approaches 1, and the influence coefficient of digital finance on the innovation patent output of enterprises is -0.0779 (1.4510-1.5289). The innovation patent output decreases by 0.078 every time the digital inclusive finance index increases by 0.1.

In addition, the smoothing parameter of this model is 0.3348, which indicates that the transformation between the mechanisms of the model is particularly smooth and slow. When the digital inclusive finance index is small, the development of digital inclusive finance will have a positive impact on the technological innovation of enterprises. In the early stage of digital finance development, the promotion of inclusive finance will help enterprises innovate, but with the continuous development of digital finance and the increasing financial scale, the influence coefficient will show a downward trend until it becomes negative. Therefore, the impact of digital financial development on enterprise technological innovation presents an inverted U-shaped relationship, which first rises and then falls, which is consistent with the theoretical analysis results of this paper.

When the development of digital inclusive finance exceeds a certain degree, its positive influence on technological innovation will be weakened. If the development of digital inclusive finance relies solely on the expansion of coverage and the excessive convenience of financial digital application, it will be difficult for the expansion of financial scale to keep the continuous incentive to technological innovation. On the basis of empowering digital technology and integrating big-technology platform technology, it can achieve a sustained positive impact on technological innovation (table 4).

Table 4. Parameter estimation results

Test statistics	Linear part	Nonlinear part
DIF	1.4510*** (0.3278)	-1.5289*** (0.5086)
Age	0.0487 (0.0386)	-0.2824*** (0.1041)
Roe	0.0180 (0.6899)	-0.2955 (1.7977)
Lev	-0.3763 (0.4585)	-0.6937 (1.3017)
Fixr	-1.5459*** (0.3710)	-0.9102 (1.0534)
Assets	0.0475 (0.0867)	1.6443*** (0.2429)
Position parameter		3.8908
Smoothing parameter		0.3348

Note: * * * and * * * indicate that the significance level is 10%, 5% and 1%, respectively, and the standard errors are in brackets.

From the perspective of the relationship between technological innovation and enterprise age, the nonlinear part is significant at the level of 1%, and the coefficient of the nonlinear part is negative, which indicates that the incentive mechanism of continuous innovation of new enterprises is not permanent, which is consistent with the view put forward by Bao (2016): the motivation of entering enterprise innovation is significantly higher than that of existing enterprises, and the innovation incentive of new enterprises is not continuously enhanced, showing an inverted U-shaped distribution trend. From the perspective of the ratio of technological innovation to noncurrent assets, the linear part is significant at the level of 1%, and the coefficient of the linear part is negative, indicating that the higher the proportion of noncurrent assets, the less conducive it is to the improvement of innovation ability. From the analysis of industry characteristics, different industry types have different enthusiasm for innovation, and technology-intensive industries are more dependent on the innovation of technology and products to improve their competitiveness. From the perspective of technological innovation and total assets, the nonlinear part is significant at the level of 1%, and the coefficient of the nonlinear part is positive, which shows that larger enterprises can support R&D activities, and technology-intensive enterprises and larger enterprises also have higher innovation performance.

4.3.3. Subsample Inspection and Result Analysis

To explore whether the promotion effect of digital inclusive finance on the technological innovation of enterprises is more significant in small and medium-sized enterprises, this paper screens all sample data and selects companies listed on GEM and SME boards for subsample regression. After data preprocessing, we finally select 575 stocks and obtain an observation sample of 4600 "enterprise-years". First, the model is tested by Wald tests, Fisher tests, and LRT tests. Through the heterogeneity test, it is determined that the number of optimal location parameters m and the number of optimal transfer functions r are both 1, and the results are shown in the following table 5.

When r=1 and m=1, this paper tests the subsamples, and the results show that at a 1% significance level, the explanatory variable DIF is significant in the linear part, and the coefficient is positive. At a 5% significance level, the explanatory variable DIF is significant in the nonlinear part, and the coefficient is negative. The influence of digital inclusive finance on the technological innovation of small and medium-sized enterprises is nonlinear, and its threshold value is c=4.1526, which is larger than that of the whole sample. When the digital inclusive finance index is lower than 4.1526, the transfer function approaches zero, and the influence coefficient of digital finance on the innovation patent output of enterprises is 0.9576. Every time the digital inclusive finance index increases by 0.1, the innovation patent output increases by 0.0958. When the digital inclusive finance index reaches 4.1526, the conversion function value is 0.5, and the influence coefficient of digital finance on the innovation patent output of enterprises is -0.6725 (0.9576-0.5*3.2601). At this time, the innovation patent output decreases by 0.0673 every time the digital inclusive finance index increases by 0.1. When the digital inclusive finance index is greater than 4.1526, the conversion function value approaches 1, and the influence coefficient of digital finance on the innovation patent output of enterprises is

Table 5. Cross-section heterogeneity test of the sample panel smoothing threshold regression model

Inspection type	assumed condition	Test statistics	m=1	m=2
Cross-section heterogeneity test	H0:r=0 H1:r^{3}1	LM	29.400*** (0.000)	37.558*** (0.000)
		LMF	4.309*** (0.000)	2.753*** (0.001)
		LRT	29.495*** (0.000)	37.712*** (0.000)
Residual heterogeneity test	H0:r=1 H1:r^{3}2	LM	5.819 (0.444)	10.316 (0.588)
		LMF	0.846 (0.534)	0.749 (0.703)
		LRT	5.823 (0.443)	10.328 (0.587)

-2.3025 (0.9576-3.2601). The innovation patent output decreases by 0.2303 every time the digital inclusive finance index increases by 0.1.

The two results show that when the development of digital inclusive finance exceeds a certain level, the technological innovation of small and microenterprises is more likely to be restrained, and it fluctuates greatly in the process of transformation, which indicates that digital inclusive finance has a more obvious impact on small and medium-sized enterprises. In addition, the smoothing parameter of this model is 0.8845. Compared with the whole sample, the sample conversion of small and microenterprises fluctuates greatly, and the speed increases. It can be seen that digital inclusive finance will have a more obvious impact on the "tail" small and microenterprises with its advantages of high efficiency and low cost (table 6).

Table 6. Estimation results of subsample parameters

Test statistics	Linear part	Nonlinear part
DIF	0.9576*** (0.2706)	-3.2601** (1.1370)
Age	0.4150*** (0.0877)	-0.5492 (0.3115)
Roe	0.8024 (0.4522)	-1.7521 (1.7195)
Lev	-0.8616*** (0.2670)	1.5689 (1.4229)
Fixr	-1.2118*** (0.2361)	0.3270 (1.3131)
Assets	0.3275*** (0.0603)	1.1741*** (0.2894)
Position parameter	4.1526	
Smoothing parameter	0.8845	

Note: * * * and * * * indicate that the significance level is 10%, 5% and 1%, respectively, and the standard errors are in brackets.

4.3.4. Subdivision Dimension Test and Results Analysis

This paper further tests the difference in the nonlinear influence of the three dimensions of digital inclusive finance on the technological innovation of enterprises: coverage breadth (V1), use depth (V2) and digitalization degree (V3). In the segment dimension test, the model is tested by Wald tests, Fisher tests and LRT tests. After the heterogeneity test, it is determined that the number of optimal position parameters m and the number of optimal conversion functions r are both 1, and the results are shown in the following table 7.

When r=1 and m=1, this paper applies the PSTR model to regress the three dimensions of digital inclusive finance: coverage (V1), depth of use (V2), and degree of digitization (V3). The empirical results are shown in the following table 8.

Judging from the coverage of digital inclusive finance, the results show that at the significance level of 1%, the explanatory variable DIF is partially significant in linearity, and the coefficient is negative. The influence of digital inclusive finance coverage on enterprise technological innovation is nonlinear with a threshold value of c=4.6961. In addition, the smoothing parameter of the model is 0.0918, indicating that the transition between the model mechanisms is very smooth and slow. The results show that the promotion effect of digital inclusive finance on the technological innovation of

Table 7. Heterogeneity test of the subdivision section

Test statistics	V1	V2	V3	And that recognition result of mechanism conversion function.
Wald Tests	99.418*** (0.000)	71.018*** (0.000)	56.603*** (0.000)	r=1,m=1
Fisher Tests	14.617*** (0.000)	10.424*** (0.000)	8.291*** (0.000)	r=1,m=1
LRT Tests	99.853*** (0.000)	71.300*** (0.000)	56.744*** (0.000)	r=1,m=1

Table 8. Estimation results of subdivision parameters

Test statistics	V1		V2		V3	
	Linear part	Nonlinear part	Linear part	Nonlinear part	Linear part	Nonlinear part
DIF	-1.8792*** (0.6357)	-1.4689 (1.2946)	4.6551*** (1.1821)	2.9676** (1.0558)	0.8722*** (0.181)	-0.7871** (0.353)
Age	0.3977*** (0.1384)	-1.0301*** (0.3164)	0.2341*** (0.1379)	-0.3617** (0.1739)	-0.0212 (0.0204)	-0.0960 (0.0593)
Roe	0.5694 (2.7251)	-1.4935 (6.1592)	0.4493 (2.9579)	-0.6904 (3.6936)	-0.0579 (0.3036)	-0.0051 (0.7799)
Lev	1.2886 (1.9269)	-4.3873 (4.4419)	0.7080 (2.0531)	-1.6791 (2.6056)	-0.6649*** (0.1687)	0.0895 (0.5411)
Fixr	-0.6675 (1.5568)	-2.7711 (3.5897)	-1.4725 (1.6701)	-0.4814 (2.1212)	-1.5624*** (0.1394)	-1.1053 (0.4398)
Assets	-2.0595*** (0.3573)	6.1655*** (0.8207)	-1.8184*** (0.3795)	3.1002*** (0.4806)	0.4919*** (0.0323)	0.5152*** (0.1005)
Position parameter	4.6961		4.0050		3.9780	
Smoothing parameter	0.0918		0.2198		0.7919	

enterprises is not due to the breadth of coverage, which is the same as Wu (2021). The promotion effect is due to the depth of use of inclusive finance rather than the breadth of coverage.

From the use depth of digital inclusive finance, the results show that at the level of 1% significance, the explanatory variable DIF is linear, and the coefficient is positive. At the 5% significance level, the explanatory variable DIF is significant in the nonlinear part, and the coefficient is positive. The influence of digital inclusive finance usage depth on enterprise technological innovation is nonlinear, and its threshold value is c=4.0050. In addition, the smoothing parameter of the model is 0.2198, which indicates that the transformation between the model mechanisms is very smooth and slow. The results show that the depth of digital inclusive finance has a significant positive effect on the technological innovation of enterprises. Therefore, in the digital finance drive of enterprise innovation, it is far from enough to only pay attention to the coverage of digital inclusive finance services in quantity, and it is necessary to deeply explore the diversity of its services and focus on its in-depth development.

From the digital support degree of digital inclusive finance, at the level of 1% significance, the linear part of the explanatory variable DIF is significant, and its coefficient is positive. At the 5% significance level, the explanatory variable DIF is significant in the nonlinear part, and the coefficient is negative. The digital support degree of inclusive finance has a nonlinear influence on enterprise technological innovation, and its threshold value is c=3.9780. In addition, the smoothing parameter of the model is 0.7919, which indicates that the transformation between the model mechanisms is very smooth and slow. The result is similar to the influence characteristics of the digital inclusive finance index. When the degree of digitalization is small, enhancing its intensity has a positive impact on the technological innovation of enterprises. In the early stage of the development of digital inclusive finance, enhancing the degree of digitalization is conducive to enterprise innovation. However, with the continuous improvement of the degree of digitalization, the problem of insufficient supervision easily leads to a credit crisis, which makes the impact coefficient show a downward trend or even a negative value, and the overall impact shows an inverted U-shaped relationship that rises first and then falls.

5. RESEARCH CONCLUSIONS AND POLICY RECOMMENDATIONS

5.1. Research Conclusion

Based on Schumpeter's multisectoral endogenous growth model and the AK model, this paper constructs a mathematical model to analyze the influence mechanism of digital inclusive finance development on enterprise technological innovation. Then, using the panel data of A-share listed companies and the Peking University Digital Inclusive Finance Index, the panel smooth transition model is used to conduct an empirical study on the nonlinear relationship between digital inclusive finance and the technological innovation. The results are as follows:

(1) From the point of view of the mathematical model, the development of digital inclusive finance leads to the trend of financial friction decreasing first and then increasing. Financial friction leads enterprises to have financing constraints, which affects the technological innovation of enterprises, making the impact of digital inclusive finance development on the technological innovation of enterprises show an "inverted U-shaped" relationship, which is promoted first and then suppressed.
(2) From the empirical test results, the development of digital inclusive finance has a nonlinear influence on the technological innovation of enterprises, and the threshold value is c=3.8908. When the digital inclusive finance index is small, it has a positive impact on promoting the technological innovation of enterprises. In the early stage of the development of digital inclusive finance, promoting inclusive finance is conducive to enterprise innovation. However, with the continuous development of digital inclusive finance and the increasing financial scale, the influence coefficient shows a downward trend until it becomes negative, and the influence of digital development in inclusive finance on the technological innovation of enterprises presents an inverted U-shaped relationship of first promoting and then restraining. Moreover, the use depth of digital inclusive finance, rather than coverage, plays a promoting role in this process. In addition, with its advantages of high efficiency and low cost, it will have a more obvious impact on "tail" small and microenterprises.

5.2. Policy Recommendations

First, focus on the development of digital inclusive finance and improve the development system. Policy-makers should continue to establish and improve the inclusive financial system, strengthen the inclusive finance policy, promote the development of inclusive finance with the aid of multidimensional digital technology, and enhance inclusive finance's ability to serve small and medium-sized enterprises to better play its role in alleviating the financial exclusion and financing difficulties of small and medium-sized enterprises, stimulate their innovation power, and as the main force of innovation, help small and medium-sized enterprises to release greater vitality. At present, traditional inclusive finance is still playing an important role, but its ability to improve technological innovation and the financial environment is still limited due to high costs and insufficient diversification. Based on traditional inclusiveness, digital inclusive finance has further absorbed the advantages of digital technology. At present, policy departments should formulate corresponding laws and regulations, and provide more innovative digital inclusive finance products and promote more financial resources to "long tail" enterprises.

Second, the supervision and management system of digital inclusive finance should be improved. At present, there are some problems in the development of digital finance, such as inadequate understanding, imperfect supervision, and loopholes in legal provisions. Under the background of rapid development in inclusive finance, the lack of corresponding management will bring huge risks to the primary and secondary financial markets and related subjects. Digital finance has both advantages and disadvantages. If it develops reasonably, it will make the market full of vitality, but excessive abnormal development can also cause abnormal development and confusion in the market. Establishing a new era digital supervision system is of great significance to avoid the abnormal development of digital inclusive finance, improve the quality of serving the real economy.

Third, the patent evaluation system should be improved. Low- and medium-quality innovation activities are not conducive to the long-term development of enterprises, nor can they provide effective support for Chinese economic development or even a waste of public resources within enterprises and society. Therefore, high-quality economic development needs to improve not only the quantity of innovation but also the quality of innovation. Therefore, it is necessary to improve the standards and requirements of patent quality examination, formulate accurate innovation incentive policies, encourage small and medium-sized enterprises to carry out high-quality innovation and make the most reasonable use of the financial support provided by digital inclusive finance.

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