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Article

Digital patenting, R&D dynamics, and the economic foundations of sustainable development: Evidence from Chinese listed firms

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Abstract: Digital patents have become an increasingly prominent form of technological activity at the firm level, but their significance for sustainable development depends on whether digital knowledge can be transformed into sustained productivity improvement, industrial upgrading and innovation capabilities. This study reassesses the relationship between digital patents, R&D investment and total factor productivity of Chinese listed companies. The study does not regard productivity as a narrow result of firm performance, but interprets it as the economic basis for sustainable industrial development, productive employment and the achievement of Sustainable Development Goals 8 and 9. Research results show that firms with high digital patenting intensity tend to have higher total factor productivity, while simply distinguishing between firms with and without digital patents provides weaker evidence. This finding shows that the depth of digital technology accumulation is more important than the existence of digital patent activity itself. In addition, the analysis also challenges the view that R&D investment has a direct positive mediating effect on productivity. Digital patents and R&D investment seem to promote each other over time, but the impact of additional R&D investment on short- and medium-term productivity is negative, indicating the existence of adjustment costs, experimentation burdens and delayed returns. The productivity relevance of digital patenting is also uneven: It is stronger among non-state-owned firms and high-technology firms, where market incentives and absorptive capacity are more favourable. Theoretically, the study contributes to the digital innovation and sustainable development literature by conceptualising digital patents as capability infrastructure that supports the economic-efficiency conditions of sustainable industrial transformation. Practically, the findings suggest that firms and policymakers should not evaluate digital innovation only by patent counts or short-term R&D expenditure. Greater attention should be given to organisational flexibility, technological absorptive capacity and the time required to convert digital knowledge into productivity gains that support long-term industrial upgrading and sustainable social development.

Keywords: digital patents; sustainable industrial development; total factor productivity; R&D dynamics; industrial upgrading; SDG 8; SDG 9; Chinese listed firms

1. Introduction

Digital technologies such as artificial intelligence, big data, cloud computing and blockchain are reshaping industrial structures, organisational practices and competitive patterns [1,2]. This transformation is particularly important for China, whose development model has gradually shifted from rapid expansion towards innovation, coordination, efficiency and sustainability [3,4]. In this context, digital innovation is not only a question of firm-level competitiveness, but also a potential economic foundation for sustainable industrial development. Sustainable social development requires firms and industries to generate productivity growth, support productive employment, upgrade technological capabilities and use resources more efficiently. These objectives are closely related to Sustainable Development Goal 8, which emphasises sustained economic growth and productive employment, and Sustainable Development Goal 9, which highlights innovation, infrastructure and industrial upgrading. Digital innovation and an appropriate regulatory environment can support a greener economic transformation [5,6], while enterprises provide the organisational setting in which digital knowledge is applied to production processes, coordination routines and new business models [7]. Previous studies have shown that digitalisation is associated with lower coordination costs, faster response times and higher productivity [8–11]. Therefore, this study focuses on the economic-efficiency dimension of digital innovation. It does not regard total factor productivity (TFP) as a comprehensive measure of environmental or social sustainability, but interprets it as one of the microeconomic foundations through which digital innovation may support sustainable development, productive employment, industrial upgrading and resource-efficient growth.

The relationship between digital innovation and productivity is not automatic or cost-free. In Schumpeter's theory, innovation promotes economic change through creative destruction, market renewal and the elimination of outdated production methods [12]. As a general-purpose technology, digital technology can extend this process through data-driven optimisation, network effects and scalable applications [3,13]. Empirical research shows that digital investment and adoption are associated with higher total factor productivity (TFP), which is mainly achieved through automation, cloud-enabled coordination and supply chain restructuring [14–17]. However, the productivity paradox still exists: initial investment, testing, organisational adjustment, and delays in the formation of complementary capabilities may weaken or delay observable productivity improvements [18]. Therefore, digital patent applications may be positively related to productivity, but innovation expenditure will still incur short-term and medium-term efficiency costs.

Digital innovation at the enterprise level also faces measurement challenges [19]. Traditional financial indicators cannot directly reveal the technological content of innovation, and annual report texts may reflect management rhetoric rather than actual technological output [20]. Patent-based indicators can more directly capture accumulated technological activity, and patents related to the digital economy are increasingly being used to study digital innovation at the enterprise level [21,22]. However, three issues remain insufficiently resolved. First, existing evidence on digitalisation and productivity does not always distinguish digital technology output from broader digital investment or managerial language. This makes it difficult to identify whether digital innovation contributes to the productivity foundations of sustainable development through actual technological accumulation. Second, the temporal sequence between R&D and patenting remains ambiguous. Digital tools may reduce R&D uncertainty and promote subsequent innovation investment [15,17,23–27], but R&D itself is also a traditional antecedent of patent applications. Treating R&D only as a mediator may therefore conceal simultaneity and feedback. Third, digital benefits are unlikely to be distributed uniformly because ownership incentives, absorptive capacity and organisational flexibility differ across firms. Research on labour demand, transparency and corporate social responsibility/environmental, social and governance practices further shows that the consequences of digitalisation are conditional and multidimensional [28–37]. While these broader outcomes provide essential context for sustainable social development, the present analysis focuses specifically on the economic-efficiency channel through which digital patenting may support productivity growth and industrial upgrading.

Against this background, this study treats digital patenting as an observable trace of firms accumulated digital technological knowledge, rather than as a direct guarantee of productivity improvement. This distinction is important because the productivity value of digital innovation depends not only on whether a firm files digital patents, but also on whether such technological activity can be converted into more efficient production, coordination and organisational routines. Therefore, this analysis first examines whether more intensive digital patent applications are related to higher total factor productivity of firms after considering observable firm characteristics and common year, industry, and provincial conditions. Then, this analysis turns to the temporal relationship between digital patent applications and R&D investment. Digital patents may reflect a stock of technological capabilities, which can promote subsequent innovation investment; however, R&D may also be a prerequisite investment for subsequent digital patent applications. This two-way relationship makes it necessary for us to go beyond the simple positive mediation framework and consider whether R&D is related to temporary adjustment costs before achieving any productivity improvement. Finally, this study examines whether the relevance of digital patent applications to productivity varies across firms. Differences in ownership incentives, market constraints, and technological absorptive capacity may affect the efficiency of firms in converting digital knowledge into economic efficiency. By considering these issues comprehensively, this study regards digital patent applications as a process related to capabilities, rather than an engine for automatically improving productivity. Its economic value depends on temporal conversion and firm-level conditions.

This study uses unbalanced panel data of China's A-share listed companies from 2008 to 2021 to link patent applications related to the digital economy with total factor productivity, and evaluates the different temporal sequences between R&D investment and digital patenting. The study makes three main contributions. First, it extends the sustainable development literature by providing firm-level evidence on how digital technological output is associated with productivity improvement, which is interpreted here as an economic foundation of sustainable industrial development rather than as a purely private performance outcome. This contribution is directly relevant to the productive employment and industrial innovation objectives embedded in Sustainable Development Goals 8 and 9. Second, the lag structure and formal bootstrap test advance the traditional one-way mediation hypothesis by proposing a dynamic explanation: digital patent applications predict subsequent R&D activities, R&D activities predict subsequent patent applications, and the R&D-related indirect effect on productivity is negative during the observation period. This finding highlights the adjustment costs that may accompany innovation-driven upgrading before longer-term productivity gains are realised. Third, the study examines whether digital productivity benefits vary according to ownership and technology-intensity groups, thereby revealing the uneven distribution of digital dividends. This heterogeneity is important for sustainable social development because productivity-enhancing digital innovation may not automatically benefit all firms or sectors equally. In view of the limited first-stage relevance and the lack of precision in the second stage, the historical-postal instrumental-variable analysis is regarded as a supplementary sensitivity check, not the main identification strategy. Section 2 describes the data and methods, Section 3 reports the empirical results, Section 4 discusses their significance and limitations, and Section 5 concludes.

2. Methods

2.1. Data and sample

The empirical analysis of this study is based on the firm-year panel data we have built, and we link digital patent application activities with productivity at the firm level. Each observation corresponds to a firm-year. In this study, total factor productivity (TFP) is regarded as an economic efficiency indicator related to sustainable development, rather than a direct or complete measure of sustainable productivity.

The analytical dataset is constructed from a processed firm-level dataset, which integrates financial, governance, research and development, and patent information. Financial and governance variables at the firm level come from CSMAR, R&D expenditure data from CNRDS, and patent information (including patent applications related to the digital economy) comes from WinGo. All estimations are based on the analytical files generated after these matched data sources have been cleaned.

The initial dataset includes 31,709 firm-year observations of Chinese A-share listed companies from 2008 to 2021. After listwise deletion for the variables required by the complete model, the full baseline regression uses 30,168 observations. Since R&D intensity is not observed for all firms, the sample size used by R&D-related models is relatively small; the lagged mechanism tests use 19,925 complete firm-year observations. Continuous variables are winsorized at the 1st and 99th percentiles.

2.2. Variables and measurements

The main outcome is measured using total factor productivity. The primary metric relies on the Levinsohn-Petrin semi-parametric technique (TFP_LP), which addresses simultaneity in production-function estimation by using intermediate inputs as proxies for unobserved productivity shocks [38]. As a robustness outcome, total factor productivity estimated by the Olley-Pakes method (TFP_OP) is also utilized, which uses investment decisions to address similar endogeneity concerns [39]. The TFP variables are taken from the cleaned firm-level analytical file. The underlying production-function estimation uses operating revenue as the output measure, fixed assets or capital-stock information as the capital input, number of employees as the labour input, intermediate inputs for the LP proxy variable, and investment-related information for the OP proxy variable. Variables are matched at the firm-year level within the CSMAR industry classification, observations with missing required inputs are excluded from the relevant estimation sample, and continuous variables used in the regressions are winsorized at the 1st and 99th percentiles. Conceptually, TFP is interpreted here as a productivity and economic-efficiency indicator, not as an all-encompassing measure of environmental or social sustainability.

To capture the intensity of digital technological innovation, we introduce the explanatory variable *lnDigitalPatents*. This is mathematically formulated by applying a natural logarithmic transformation to the exact count of digital economy-focused patent filings a firm submits annually:

$$lnDigitalPatents_{it} = ln\,(1 + DigitalPatentApplications_{it}) \tag{1}$$

Since patent variables are usually right-skewed and contain zero values, a logarithmic transformation is used, wherein adding one before taking the logarithm retains firms with no digital patent applications in a given year. *lnDigitalPatents* is based on annual digital-economy-related patent applications rather than granted patents. The identification of digital-economy-related patents follows the WinGo patent database's pre-classified digital-economy labels, which are constructed from its keyword and patent-classification screening rules for digital technologies. This study uses the database label directly and does not manually reclassify patent records. This measure captures the intensity of digital patenting activity and should therefore be interpreted as an observable innovation-output proxy, rather than a direct measure of patent quality, commercialization value, or realized sustainability performance.

R&D intensity (RD) is calculated by dividing R&D expenditure by operating revenue and multiplying it by 100. RD is expressed as a percentage and captures the scale of internal innovation input. To account for temporal dynamics, this study does not assume a simple contemporaneous positive mediation path. Instead, RD is treated as a dynamic mechanism variable, and the empirical tests examine whether digital patenting precedes R&D, whether R&D precedes digital patenting, and whether R&D has short- or medium-run productivity costs.

The empirical models incorporate non-mediating firm-level controls, including firm age, operating-revenue growth, leverage, firm size, Tobin's Q, profitability, current ratio, cash ratio, board size and ownership. Firm size is measured as the logarithm of one plus the number of employees, firm age is measured as the logarithm of firm age, and ownership is coded as one for state-owned enterprises and zero otherwise. The definitions, measurements, and sources of all variables are summarized in **Table 1**.

Table 1. Variable definitions and measurement.

Variable type	Variable name	Symbol	Measurement	Source
Dependent variable	Total factor productivity	TFP_LP	Estimated using the Levinsohn-Petrin method	CSMAR; author's calculation
Robustness dependent variable	Total factor productivity	TFP_OP	Estimated using the Olley-Pakes method	CSMAR; author's calculation
Main explanatory variable	Digital patenting activity	*lnDigitalPatents*	ln (1 + annual digital-economy-related patent applications)	WinGo
Alternative explanatory variable	Digital innovation dummy	Digital_Dummy	1 if the firm has at least one digital-economy-related patent application; 0 otherwise	WinGo
Dynamic mechanism variable	R&D intensity	RD	R&D expenditure / operating revenue x 100	CNRDS

Table 1. (*Continued*).

Variable type	Variable name	Symbol	Measurement	Source
Control variable	Firm age	lnAge	ln (firm age)	CSMAR
Control variable	Firm growth	Growth	Operating-revenue growth rate	CSMAR; author's calculation
Control variable	Leverage	Lev	Total liabilities / total assets	CSMAR
Control variable	Firm size	lnSize	ln (1 + number of employees)	CSMAR
Control variable	Tobin's Q	TobinQ	Tobin's Q value	CSMAR
Control variable	Profitability	Profitability	Net profit / operating revenue	CSMAR; author's calculation
Control variable	Current ratio	CurrentRatio	Current assets / current liabilities	CSMAR
Control variable	Cash ratio	CashRatio	Cash holdings / current liabilities	CSMAR
Control variable	Board size	lnBoardSize	ln (number of board directors)	CSMAR
Control variable	Ownership	SOE	1 for state-owned enterprises; 0 otherwise	CSMAR

Note: This table summarises the definitions, measurements and data sources of the variables used in the empirical analysis.

2.3. Empirical model

Based on the variables defined above, the baseline model estimates the association between digital patenting activity and firm-level total factor productivity. The empirical specification is as follows:

$$TFP_{it}=\alpha+\beta\, ln\, DigitalPatents_{it}+\gamma' X_{it}+\lambda_t+\delta_{j(i)}+\theta_{p(i)}+\varepsilon_{it} \tag{2}$$

where TFP_{it} denotes total factor productivity of firm i in year t; $lnDigitalPatents_{it}$ is the logged digital patenting intensity of firm i in year t; X_{it} is a vector of non-mediating firm-level controls; λ_t, $\delta_{j(i)}$ and $\theta_{p(i)}$ denote year, industry and province fixed effects, respectively; and ε_{it} is the error term.

The model reduces bias from observable firm characteristics, common year shocks, industry-specific conditions and time-invariant provincial differences. The specification does not include firm fixed effects, because the main design focuses on cross-firm and within-industry/province variation in digital patenting while controlling for firm-level observables and fixed contextual dimensions. This choice, however, should be interpreted as a limitation. Unobserved firm-level characteristics, such as managerial quality, innovation culture, internal data capabilities, organisational routines or long-standing strategic orientation, may still be correlated with both digital patenting and productivity. The baseline estimates are therefore interpreted as conditional associations rather than firm-level causal effects.

2.4. Mediation model

To examine the R&D-related mechanism, this study estimates temporal-ordering models rather than relying on a purely contemporaneous mediation design. This dynamic approach accounts for the inherent logic of innovation processes, given that *R&D* investment often precedes patent output, rendering a purely contemporaneous causal chain potentially counterintuitive.

First, the total-effect model estimates whether lagged *lnDigitalPatents* is associated with subsequent TFP:

$$TFP_{it}=\alpha+c\ ln\,DigitalPatents_{i,t\text{-}1}+\gamma' X_{it}+\lambda_t+\delta_{j(i)}+\theta_{p(i)}+\varepsilon_{it} \tag{3}$$

Second, *R&D* intensity is regressed on lagged *lnDigitalPatents* to test whether existing digital patenting activity is followed by higher innovation input:

$$RD_{it}=\alpha+a\ ln\,DigitalPatents_{i,t\text{-}1}+\gamma' X_{it}+\lambda_t+\delta_{j(i)}+\theta_{p(i)}+\varepsilon_{it} \tag{4}$$

Third, *TFP* is regressed on both lagged *lnDigitalPatents* and current RD to evaluate the direct association of digital patenting and the productivity implication of *R&D* intensity:

$$TFP_{it}=\alpha+c'\,ln\,DigitalPatents_{i,t\text{-}1}+bRD_{it}+\gamma' X_{it}+\lambda_t+\delta_{j(i)}+\theta_{p(i)}+\varepsilon_{it} \tag{5}$$

where the fixed-effects structure follows the baseline model. A positive mechanism would require *lnDigitalPatents* to predict RD and RD to predict *TFP* in the same direction as the hypothesized productivity channel. If RD is negative in the final equation, the indirect effect is interpreted as an adjustment-cost or delayed-payoff channel rather than as positive mediation.

To evaluate the indirect effects more explicitly, this study reports 5000 firm-cluster bootstrap replications for the product of two estimated coefficients: the effect of digital patenting on *R&D* intensity, and the subsequent effect of *R&D* intensity on total factor productivity. In addition, reverse temporal-ordering models estimate whether *RD(t-1)* predicts *lnDigitalPatents(t)*, thereby testing whether prior *R&D* investment may be an antecedent of digital patenting.

2.5. Endogeneity, robustness and heterogeneity checks

Although the baseline specification controls for non-mediating firm characteristics and year, industry and province fixed effects, endogeneity may still arise from reverse causality, unobserved firm-level heterogeneity and unobserved time-varying regional conditions. The analysis therefore treats the instrumental-variable evidence as a sensitivity check, not as conclusive causal proof:

$$IV_{it}=Post\mathrm{Office1984}_{p(i)}\times \mathrm{Year}_t \tag{6}$$

where the instrument interacts the number of post offices in province p in 1984 with year dummy variables, with one year omitted as the reference category. This construction captures historical communications infrastructure that may shape later digital diffusion, while allowing its relevance to vary over time.

The exclusion restriction is potentially vulnerable because historical postal infrastructure may also proxy for long-run provincial development. To address this issue, the IV specification adds historical provincial development controls, including 1984 population, road availability and higher-education resources, interacted with year indicators. These controls reduce, but cannot eliminate, concerns about the historical-development channel.

Both 2SLS stages retain the baseline firm controls and year, industry and province fixed effects, and standard errors are clustered at the firm level. To evaluate the validity of the instrumental variable, this study reports the first-stage joint excluded-instrument statistics and over-identification tests.

Several robustness checks are implemented. First, the dependent variable is replaced with *TFP_OP* to test whether the findings depend on the productivity estimator. Second, *lnDigitalPatents* is lagged by one year to reduce simultaneity concerns. Third, *lnDigitalPatents* is replaced with a digital-innovation dummy. Fourth, information-technology firms are excluded to test whether the results are specific to firms whose core business is digital technology.

A placebo test is also conducted by randomly redistributing *lnDigitalPatents* across firms and re-estimating the baseline regression 500 times. This test examines whether the observed association is likely to arise from random allocation rather than from the realized distribution of digital patenting activity.

Finally, stratified subsample estimations examine whether digital dividends are distributed unevenly. Our analysis compares state-owned and non-state-owned enterprises, as well as high-technology and non-high-technology firms, to identify boundary conditions related to ownership structure and absorptive capacity.

3. Results

3.1. Descriptive statistics

Comprehensive summary statistics for the focal variables are reported in **Table 2**. The eligible panel contains 31,709 firm-year observations. The mean LP-based productivity index is 8.344 with a standard deviation of 1.058, while the OP-based productivity index has a mean of 6.656 and a standard deviation of 0.887.

Table 2. Descriptive statistics.

Variable	Symbol	Definition	N	Mean	SD	Min.	Max.
Total factor productivity (LP)	TFP_LP	TFP estimated by Levinsohn-Petrin method	31,709	8.344	1.058	6.009	11.16
Total factor productivity (OP)	TFP_OP	TFP estimated by Olley-Pakes method	31,709	6.656	0.887	4.73	9.055
Digital technology innovation	*lnDigitalPatents*	ln (1 + digital-economy patent applications)	31,709	0.755	1.229	0	5.118
Firm age	lnAge	ln (firm age)	31,709	1.991	0.92	0	3.258
Firm size	lnSize	ln (1 + number of employees)	31,709	7.678	1.251	4.554	11.174
Leverage	Lev	Total liabilities / total assets	31,708	0.437	0.21	0.056	0.952
Tobin’s Q	TobinQ	Tobin’s Q value	31,159	2.103	1.393	0.865	9.042
R&D intensity	RD	R&D input / operating revenue (%)	23,511	4.785	4.688	0.03	26.788
Ownership	SOE	State-owned enterprise = 1; otherwise = 0	30,755	0.396	0.489	0	1

Note: This table reports the descriptive statistics for the variables used in the empirical analysis. SD denotes standard deviation.

The mean value of *lnDigitalPatents* is 0.755 and the standard deviation is 1.229, with a minimum value of zero. This distribution indicates that digital patenting activity among Chinese listed firms is unevenly distributed. R&D intensity is observed for 23,511 firm-year observations, with a mean of 4.785 percent and a standard deviation of 4.688.

3.2. Baseline results: Digital patenting and productivity

Table 3 reports the baseline estimates linking digital patenting activity to TFP_LP. The unconditional association is positive and significant. After the full set of controls and fixed effects is introduced, the coefficient becomes much smaller but remains positive and statistically significant in the preferred specification with year, industry and province fixed effects.

Table 3. Baseline regression results.

	(1)	**(2)**	**(3)**	**(4)**
Dependent variable	TFP_LP	TFP_LP	TFP_LP	TFP_LP
lnDigitalPatents	0.117*** (0.014)	0.002 (0.008)	0.037*** (0.007)	0.033*** (0.007)
lnAge		0.179*** (0.011)	0.109*** (0.010)	0.121*** (0.010)
Growth		-0.022*** (0.008)	-0.020*** (0.007)	-0.018*** (0.007)
Lev		1.014*** (0.064)	0.771*** (0.056)	0.813*** (0.054)
lnSize		0.456*** (0.011)	0.473*** (0.010)	0.470*** (0.009)
TobinQ		-0.090*** (0.007)	-0.062*** (0.007)	-0.061*** (0.006)
Profitability		0.795*** (0.045)	0.709*** (0.040)	0.691*** (0.039)
Current ratio		1.683*** (0.067)	1.617*** (0.060)	1.603*** (0.059)
Cash ratio		-0.333*** (0.082)	-0.319*** (0.073)	-0.344*** (0.072)
lnBoardSize		0.006 (0.052)	0.091** (0.043)	0.099** (0.041)
SOE		0.033 (0.026)	0.042* (0.023)	0.045** (0.022)
Year fixed effects	No	No	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Province fixed effects	No	No	No	Yes
Observations	31,709	30,168	30,168	30,168
R-squared	0.019	0.563	0.691	0.707
Clustered Wald statistic	71.33	548.61	52.99	67.45

Note: Firm-cluster robust standard errors are reported in parentheses. *, ** and *** indicate significance at the 10 %, 5 % and 1 % levels, respectively.

The preferred baseline coefficient is 0.033 and statistically significant at the 1 % level. This result supports a positive association between digital patenting activity and firm-level productivity, but it also shows that a large share of the raw association is absorbed by firm characteristics and fixed contextual factors. The result is interpreted as productivity evidence.

Figure 1 illustrates how the *lnDigitalPatents* coefficient changes across baseline specifications. The coefficient declines sharply once controls and fixed effects are added, but the fully adjusted estimate remains positive. This pattern is consistent with a conditional digital-productivity relationship rather than an automatic transformation of digital innovation into sustainability performance.

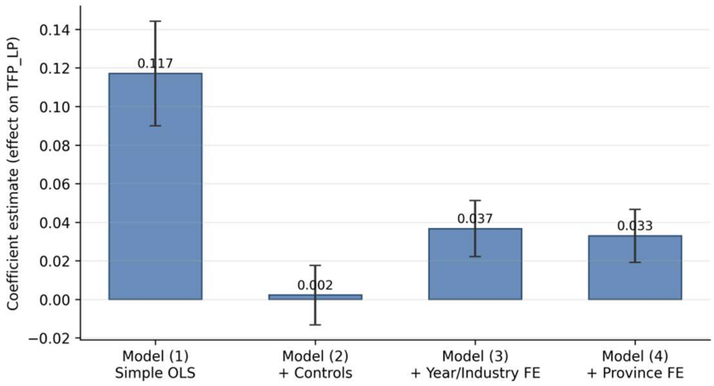

Figure 1. Stability of the *lnDigitalPatents* coefficient across baseline specifications.
Note: Error bars represent 95 % confidence intervals.

3.3. Endogeneity and robustness checks

Although the baseline specification controls for firm characteristics and year, industry and province fixed effects, reverse causality and omitted time-varying regional conditions remain possible. **Table 4** therefore reports the historical-postal 2SLS specification and a stricter version that additionally interacts 1984 provincial population, road availability and higher-education intensity with year indicators. The joint excluded-instrument statistics are 16.07 (p = 0.245) in the baseline historical-postal IV specification and 14.32 (p = 0.352) after the provincial development controls are added. These results indicate weak first-stage relevance and require cautious interpretation of the second-stage estimates.

Table 4. Endogeneity and robustness checks.

Panel / test	**Specification**	**Core variable**	**Coefficient / statistic**	**Std. error / *p*-value**
Panel A: 2SLS second stage	Baseline historical-postal IV	*lnDigitalPatents*	-0.414*	(0.248)
Panel A: 2SLS second stage	Historical-postal IV with provincial development controls	*lnDigitalPatents*	0.326	(0.271)
Panel A: First-stage diagnostics	Baseline historical-postal IV	Joint excluded-instrument statistic	16.07	p = 0.245
Panel A: First-stage diagnostics	Historical-postal IV with provincial development controls	Joint excluded-instrument statistic	14.32	p = 0.352
Panel A: Over-identification	Historical-postal IV with provincial development controls	Wooldridge score test	6.74	p = 0.874
Panel B: Alternative productivity estimator	Dependent variable: TFP_OP	*lnDigitalPatents*	0.038***	(0.007)
Panel B: Lagged explanatory variable	Dependent variable: TFP_LP	*L.lnDigitalPatents*	0.030***	(0.008)
Panel B: Alternative explanatory variable	Dependent variable: TFP_LP	*Digital_Dummy*	0.018	(0.014)
Panel B: Excluding specific samples	Dependent variable: TFP_LP; excludes IT sector	*lnDigitalPatents*	0.040***	(0.008)

Note: Firm-cluster robust standard errors are reported in parentheses for coefficient estimates. For diagnostic rows, p-values are reported in the final column. *, ** and *** indicate significance at the 10 %, 5 % and 1 % levels, respectively. All specifications include non-mediating firm-level controls and year, industry and province fixed effects. Provincial development controls comprise historical population, road availability and higher-education intensity, each interacted with year indicators. The reported first-stage statistics are cluster-robust Wald tests with 13 degrees of freedom.

The baseline historical-postal specification produces an imprecise negative coefficient (-0.414, $p = 0.096$). After provincial development controls are introduced, the coefficient turns positive (0.326) but remains statistically insignificant ($p = 0.228$), with a wide confidence interval. **Figure 2** illustrates this instability relative to the positive baseline estimate. Accordingly, the IV analysis is treated as a sensitivity exercise rather than conclusive causal evidence.

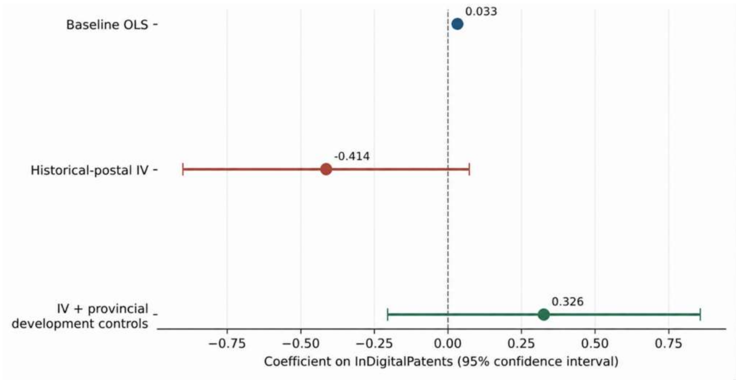

Figure 2. Baseline and instrumental-variable estimates.

Source: **Table 3** and **Table 4**.

Note: Points report coefficient estimates and horizontal lines report 95 % confidence intervals. The provincial-control specification adds historical population, road availability and higher-education intensity interacted with year indicators.

Panel B reports four robustness checks. The coefficient remains positive when *TFP_OP* is used (0.038, $p < 0.01$), when *lnDigitalPatents* is lagged by one year (0.030, $p < 0.01$), and when information-technology firms are excluded (0.040, $p < 0.01$). By contrast, the coefficient on *Digital_Dummy* is positive but statistically insignificant (0.018, $p = 0.183$). The robustness evidence therefore supports the continuous patent-intensity measure but not the binary indicator.

To assess whether the estimated association could arise from random allocation, *lnDigitalPatents* is randomly reassigned and the baseline regression is repeated 500 times. The placebo estimates are centred near zero, whereas the observed baseline coefficient of 0.033 lies in the upper tail of the placebo distribution (**Figure 3**).

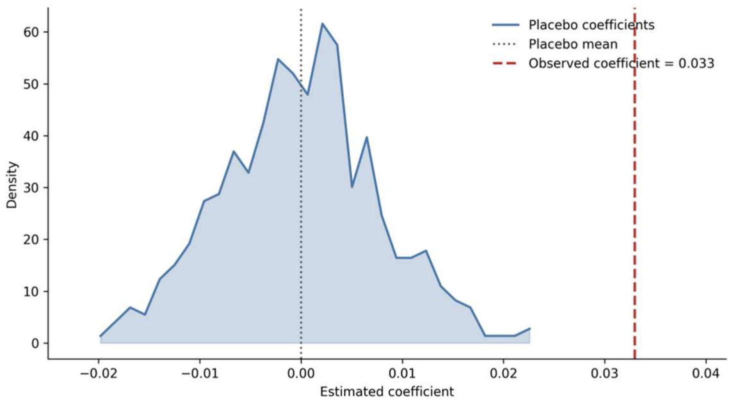

Figure 3. Placebo test results.

Note: The distribution reports coefficients from 500 placebo assignments. The red dashed line indicates the re-estimated baseline coefficient of 0.033.

3.4. Temporal ordering of R&D investment, digital patenting and productivity

A purely contemporaneous mediation framework cannot distinguish whether R&D investment precedes or follows digital patenting. To robustly evaluate these temporal dynamics, Panel A of **Table 5** utilizes lagged *lnDigitalPatents* and formally assesses the indirect effect via 5000 firm-cluster wild-bootstrap replications. The results indicate that *lnDigitalPatents(t-1)* positively predicts *RD(t)* (0.557, $p < 0.01$) while retaining a positive association with *TFP(t)* in both the total-effect and final equations.

However, *RD(t)* is negatively associated with TFP(t) after *lnDigitalPatents(t-1)* is controlled (-0.033, $p < 0.01$). The estimated indirect effect is -0.018, with a 95 % bootstrap confidence interval of [-0.023, -0.014]. Similar negative indirect effects remain when productivity is measured at t+1 and t+2. In the reverse ordering, *RD(t-1)* significantly predicts *lnDigitalPatents(t)* (0.054, $p < 0.01$). The evidence therefore does not establish *R&D* as a positive one-way mediator; instead, it indicates a bidirectional and dynamically ordered relationship in which *R&D* expenditure is associated with short- and medium-run efficiency costs.

Table 5. Temporal ordering, indirect effects and heterogeneity results.

Panel / sample	Dependent variable	Core variable	Coefficient	Std. error / statistic
Panel A: Lagged total-effect model	TFP_LP(t)	*lnDigitalPatents* (t-1)	0.021***	(0.007)
Panel A: Lagged R&D equation	RD(t)	*lnDigitalPatents* (t-1)	0.557***	(0.053)
Panel A: Final TFP equation	TFP_LP(t)	*lnDigitalPatents* (t-1)	0.039***	(0.007)
Panel A: Final TFP equation	TFP_LP(t)	RD(t)	-0.033***	(0.003)
Panel A: Bootstrap indirect effect	TFP_LP(t)	*lnDigitalPatents* (t-1) -> RD(t)	-0.018***	95 % CI [-0.023, -0.014]
Panel A: Reverse temporal ordering	*lnDigitalPatents* (t)	RD (t-1)	0.054***	(0.005)
Panel B: Non-state-owned enterprises	TFP_LP	*lnDigitalPatents*	0.048***	(0.012)
Panel B: State-owned enterprises	TFP_LP	*lnDigitalPatents*	0.019	(0.013)
Panel B: Ownership difference		*p*-value	0.028	
Panel C: High-technology enterprises	TFP_LP	*lnDigitalPatents*	0.051***	(0.012)
Panel C: Non-high-technology enterprises	TFP_LP	*lnDigitalPatents*	0.023*	(0.012)
Panel C: Industry-type difference		*p*-value	0.041	

Note: Firm-cluster robust standard errors are reported in parentheses. *, ** and *** indicate significance at the 10 %, 5 % and 1 % levels, respectively. Panel A uses a common complete-case sample and includes firm-level controls and year, industry and province fixed effects. The indirect effect is evaluated using 5000 firm-cluster wild-bootstrap replications. The negative interval does not support a positive R&D mediation mechanism.

Overall, temporal analyses show that R&D investment and digital patent applications promote each other over time, but the impact of R&D on productivity is not immediate. Digital patent applications remain positively related to productivity, and additional R&D intensity seems to incur adjustment and experimentation costs within the observed two-year period. These findings are interpreted as dynamic associations, rather than clear causal mediation chains (see **Figure 4**).

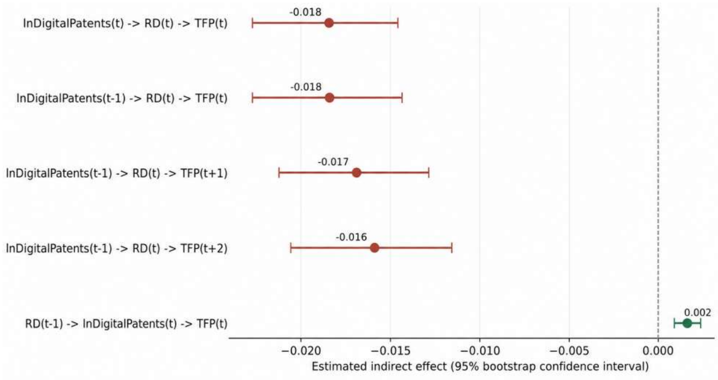

Figure 4. Indirect effects under alternative temporal orderings.

Note: Points report estimated indirect effects and horizontal lines report 95 % firm-cluster wild-bootstrap confidence intervals based on 5000 replications. Negative estimates correspond to specifications in which R&D follows digital patenting; the positive estimate reports the reverse sequence in which lagged R&D predicts digital patenting.

3.5. Uneven digital dividends: Ownership and absorptive capacity

Panels B and C of **Table 5** report the heterogeneous estimation results. The coefficient for non-state-owned enterprises is 0.048, which is statistically significant at the 1 % significance level. The estimate for state-owned enterprises is relatively small at 0.019, and is not statistically significant. The difference between different ownership groups is statistically significant, with a *p*-value of 0.028. These results show that non-state-owned enterprises are more effective in translating digital patent application activities into productivity improvements. This pattern is consistent with the following view: stronger market incentives and greater organisational flexibility may be linked to a stronger conversion of digital capabilities into productive capacity.

For high-tech enterprises, the estimated coefficient is 0.051, and it is significant at the 1 % significance level. For non-high-tech enterprises, the coefficient is 0.023, and it is significant at the 10 % significance level. The difference between the two groups is statistically significant (the *p*-value is 0.041). These results imply that technology-intensive firms are better able to translate digital patents into productivity gains. Therefore, stronger technological absorptive capacity appears to be associated with stronger productivity relevance of digital innovation (**Figure 5**).

The results of the analysis of ownership and industry heterogeneity provide the main evidence based on coefficients for the uneven distribution of digital dividends. These results show that when enterprises have stronger market incentives and technological absorptive capacity, digital patent activities can be more effectively transformed into productivity.

In general, empirical results show that digital patent application activities are positively related to firm productivity, but this relationship is not automatic or evenly distributed. For firms with stronger market incentives and better technological absorptive capacity, the productivity dividends brought by digital patents are more significant. These findings support a core argument regarding the economic-efficiency foundations of sustainable development: Digital patent applications can promote sustainable industrial upgrading by improving productivity, but they do not in themselves demonstrate broader environmental or social sustainability outcomes. These outcomes need to be directly investigated in future research.

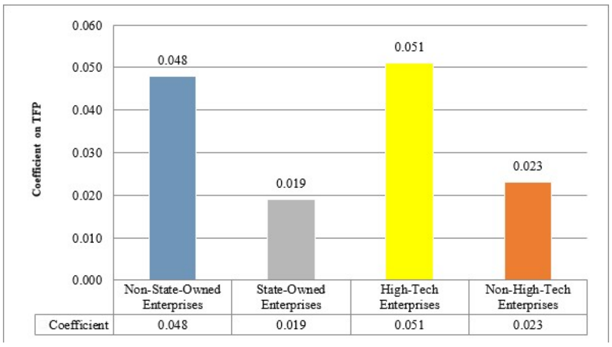

Figure 5. Uneven digital dividends by ownership and technological absorptive capacity.

Source: **Table 5**.

Note: Coefficients represent the estimated effects of *lnDigitalPatents* on TFP_LP in subsample regressions. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; *n.s.* = not significant.

4. Discussion

4.1. Digital patents as capability infrastructure

This study shows that digital patents can function as firm-level capability infrastructure, supporting a specific and focused interpretation regarding economic efficiency. Digital patenting is positively associated with TFP, an economic-efficiency outcome, rather than directly proving an increase in comprehensive sustainable productive capacity.

This interpretation is consistent with Schumpeterian innovation theory, which views technological change as a source of economic transformation and productivity renewal [12]. It also aligns with studies that describe digital technologies as general-purpose technologies and as drivers of organizational transformation [3,13]. At the same time, the smaller coefficient after controls and the weak IV evidence are consistent with productivity-paradox arguments that digital investments generate measured efficiency gains only when complementary capabilities are present [14–17]. Compared with studies that emphasize a straightforward innovation-productivity channel [18], the present evidence points to a more conditional and time-sensitive relationship. From a sustainable development perspective, this means that digital patents should be understood as enabling conditions for long-term industrial upgrading and productive capacity, rather than as automatic guarantees of sustainable performance.

4.2. R&D dynamics and the timing of innovation investment

The mechanism results provide a nuanced answer to the second research question: R&D intensity does not provide evidence of a simple, positive contemporaneous mediation channel. *LnDigitalPatents (t-1)* is positively associated with *RD (t)*, but *RD (t)* is negatively associated with *TFP (t), TFP (t+1)* and *TFP (t+2)*. The bootstrap indirect effects are therefore negative rather than positive.

Previous studies have argued that digital twins, big data analytics and digital collaboration tools can reduce the uncertainty of research and development and improve the controllability of innovation [17,23,24]. Other studies emphasise that organisational learning and absorptive capacity determine whether digital tools can be transformed into productive capabilities [15,25,26]. The results of this study have refined these views: digital patenting and R&D investment appear to be mutually associated over time, but before long-term returns are realised, R&D may initially consume resources, disrupt conventional processes and reduce measured productivity. This finding is important for sustainable industrial development because innovation-driven upgrading may require a transition period during which firms bear temporary efficiency losses before digital knowledge is converted into durable productivity gains.

4.3. Uneven distribution of digital dividends and boundary conditions

The heterogeneity results answer the third research question, showing that the distribution of digital dividends among different firms is uneven. The stronger association in non-state-owned enterprises is consistent with the following view: market competition, flexibility of incentive mechanisms and stronger performance pressure can improve the productivity value of digital innovation [4–6,40,41].

High-tech firms have a larger coefficient, which supports the absorptive capacity explanation. Firms with a stronger technical foundation can better integrate digital patents into the existing innovation and production processes. The regional digital divide may further exacerbate these differences, because firms in environments with a higher degree of digitalisation are more likely to have access to supporting infrastructure, skilled labour and data resources [9]. Therefore, the contribution of digital patenting to sustainable social development depends not only on technological accumulation inside firms, but also on the institutional, regional and organisational conditions that allow such accumulation to be transformed into productivity and industrial upgrading.

4.4. Socio-economic significance, limitations and future research direction

The research results also have broader socio-economic implications, but these implications should be interpreted carefully. This study does not claim that digital patenting directly improves environmental quality, social welfare or labour-market outcomes. Instead, its contribution to sustainable social development lies in showing how digital technological accumulation is associated with the productivity and industrial-upgrading foundations of sustainable development. Digital transformation may reshape labour demand, increase the value of technical and problem-solving skills, and change the organisational form of the workplace [21,22,28–42]. However, this study does not directly evaluate employment quality, wage structures or labour-market inclusion. Therefore, its relevance to Sustainable Development Goal 8 is mainly reflected in the productivity conditions that support productive employment and long-term economic resilience [43].

The findings are also relevant to Sustainable Development Goal 9 because digital patenting reflects firms' accumulation of innovation-related capabilities [21,22].

When such capabilities are successfully converted into productivity, they may support industrial upgrading, technological modernisation and innovation-driven growth. At the same time, the heterogeneity results show that these benefits are unevenly distributed. Non-state-owned and high-technology firms appear better able to transform digital patents into productivity gains, whereas other firms may require stronger absorptive capacity, organisational flexibility and supporting infrastructure. This imbalance is crucial to sustainable social development, because if under-prepared firms or regions cannot turn technological activities into productive results, digital transformation may widen the capability gap.

Digital innovation can also affect corporate responsibility and governance by improving traceability, transparency and stakeholder monitoring [32–34]. Relevant research further shows that digital transformation can affect corporate social responsibility and environmental, social and governance (ESG) information disclosure [35–37]. However, this study does not directly measure these social and environmental outcomes, so they are discussed as a future research direction rather than as an established empirical conclusion.

There are still some limitations in this study. First, *lnDigitalPatents* measures the number of patent applications, not the quality, commercial value or technical depth of the patent. Second, *TFP_LP* and *TFP_OP* measure productivity and economic efficiency, not comprehensive sustainable production capacity [44]. Third, after the addition of provincial development control variables, the effectiveness of the historical-postal instrumental variable has been weakened, so caution should be exercised when making causal interpretations. Fourth, the research and development results reflect dynamic adjustment costs, not a positive short-term mediation effect. Future research should cover green productivity, patent quality, employee performance and direct ESG indicators.

5. Conclusion

This study examines the relationship between digital patent applications, research and development dynamics, and total factor productivity among China's A-share listed firms from 2008 to 2021. The research adopts a panel regression model at the firm level, and incorporates firm-level control variables and the fixed effects of year, industry, and province. The results show that there is a positive correlation between the intensity of digital patent applications and productivity. Even if other productivity estimation methods are adopted, digital patent applications are lagged, and information technology firms are excluded, this conclusion is still stable. However, the results of the binary digital innovation dummy variable are not significant, which shows that the depth of digital technology accumulation is more important than the mere existence of digital patent application activity itself.

From the perspective of sustainable development, the key implication is that productivity should not only be regarded as a narrow firm performance indicator. On the contrary, the improvement of productivity is the economic foundation for sustainable industrial development, productive employment, innovation capacity, and long-term economic resilience. In this sense, digital patent applications can support the productivity foundation of Sustainable Development Goals 8 and 9, but this can only be achieved if digital knowledge can be effectively transformed into organisational and production efficiency.

The results of mechanism and heterogeneity analysis further show that this contribution is conditional. Temporal-ordering and bootstrap tests show that research and development is not a simple short-term positive mediator; on the contrary, it is related to adjustment costs and delayed productivity returns. The relevance of digital patents to productivity is also more prominent in non-state-owned firms and high-tech firms, where market incentives, organisational flexibility, and absorptive capacity are more favourable. The causal support provided by instrumental variable analysis is limited, so the research results should be interpreted as robust conditional associations, not definite causal effects.

These results show that firms and policymakers should not evaluate digital transformation only by the number of patents or short-term research and development expenditures. More attention should be paid to absorptive capacity, organisational adaptability, digital infrastructure, technical skills, and support for under-prepared firms. Future research should examine patent quality, green productivity, labour market outcomes, and corporate social responsibility/environmental, social and governance (CSR/ESG) indicators to more directly assess how digital innovation contributes to the broader environmental and social dimensions of sustainable development.

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