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Research Article

Determinants of ICT Industry Development: Evidence from Provincial Panel Data in China (2001–2023)

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Abstract

According to the balanced panel data of 31 provinces in China between 2001 and 2023, this paper empirically examines the key factors associated with information and communication technology (ICT) industry development. The results of multiple panel regressions indicate that regional economic development is the most consistent factor associated with ICT development across model specifications, which is consistently significant across all model specifications. Investment in technology has a high degree of model dependence as well as conditional heterogeneity and it is dependent on the presence of supportive regional institutions and complementary resources. On the contrary, policy-based measures do not have a uniform effect on the development of ICT in regions. This paper contributes to the literature in three aspects. First, it moves beyond conventional single-model analysis by employing a multi-model panel framework to systematically assess the robustness and model dependence of key determinants. Second, it explicitly examines the conditional and heterogeneous effects of technological investment, highlighting its reliance on complementary institutional and resource conditions. Third, it provides additional empirical evidence on the limited short-term associations of policy variables with ICT development, emphasizing the distinction between policy quantity and policy quality. These contributions offer a more nuanced understanding of ICT development dynamics across Chinese provinces.

Keywords

ICT industry, Endogenous influencing factors, Provincial heterogeneity, Panel regression, China

1. Introduction

The information and communication technology (ICT) manufacturing industry, as one of the fundamental pillars of the digital economy, has become a key driver of industrial digitalization and digital infrastructure development worldwide. 2001 was a watershed year in the history of China and its ICT sector since it joined the World Trade Organization (WTO), offering unparalleled market expansion opportunities and catching up on technology (Chen and Cai, 2019). In the last twenty years, China has constructed the biggest 5G network in the world, and the share of the digital economy in the country is now more than 40 percent of the gross domestic product (GDP).

Regardless of such impressive accomplishments, there are three critical problems that the ICT sector in China must deal with: a high imbalance in regional development (Wen et al., 2023), constraints in the form of core technologies caused by the global technological blockades (Zhang et al., 2026), and inability to create sufficient endogenous innovation (Chen et al., 2024). In the context of the transformation of the global industrial chain and growing tech competition, this study aims to examine the statistical associations between regional economic development, technological investment, policy variables, and ICT industry development across Chinese provinces.

Existing studies on China's ICT industry and digital economy have primarily focused on either aggregate national trends or single-model estimations, often emphasizing the positive role of economic development and technological inputs. However, limited attention has been paid to the model sensitivity, conditional effects, and regional heterogeneity of these determinants. In particular, whether technological investment and policy variables exert stable and consistent effects across different empirical specifications remains underexplored.

To address this gap, this study does not aim to reconfirm well-established relationships, but rather to re-examine their robustness, conditionality, and heterogeneity using a multi-model panel framework. By comparing random effects, fixed effects, and Tobit estimations, this paper identifies which determinants are structurally stable and which are model-dependent.

Therefore, the main contribution of this study lies in providing a robustness-oriented and heterogeneity-sensitive empirical reassessment of ICT development drivers, offering new insights into why some commonly assumed factors fail to exhibit stable effects across regions and model specifications. Based on the existing literature, this study expects that regional economic development is positively associated with ICT industry development, while the effects of technological investment and policy-related variables may exhibit conditional heterogeneity and model dependence across different empirical specifications.

2. Research Methodology

2.1. Model Specification

The multiple panel regression analysis has been used in this study to identify the association of explanatory variables with the ICT development. The overall log-linear regression formula is given by:

$$\ln(Y_t) = A + B\ln(X_{1t}) + C\ln(X_{2t}) + \cdots + DX_{kt} + \epsilon_t \tag{1}$$

where Yt is the variable being explained, X1t to Xkt are explanatory variables, alpha0 to alpha k are regression coefficients, and the error term is epsilon t.

In order to achieve an isolation of the endogenous effects on the development of ICT, we build the baseline model with ICT as the dependent variable:

$$\ln(ICT_t) = \alpha_0 + \alpha_1\ln(GDPcap_t) + \alpha_2\ln(TechInv_t) + \alpha_3 PolStab_t + \alpha_4 Reg_t + \epsilon_t \tag{2}$$

where i denotes province and t denotes year. μi represents province fixed effects, λt represents time fixed effects, and ϵit is the idiosyncratic error term. The introduction of double fixed effects can effectively control the unobservable individual heterogeneity of each province and the time trend effect of macroeconomic changes on the ICT industry, and reduce the estimation bias caused by missing variables to the greatest extent.

It should be noted that the empirical strategy adopted in this study is primarily designed to identify statistical relationships rather than causal effects. Although fixed effects are introduced to control for unobserved heterogeneity, potential endogeneity issues such as reverse causality and omitted variable bias cannot be fully eliminated. Therefore, the results should be interpreted as associational evidence rather than definitive causal inference.

In addition, the present empirical framework mainly focuses on contemporaneous relationships and does not explicitly model dynamic lag effects. Given that policy implementation and technological upgrading may generate delayed and cumulative impacts over time, dynamic specifications such as distributed lag models or dynamic panel estimators could provide additional insights. However, since the primary objective of this study is to examine the robustness and heterogeneity of core determinants across multiple panel specifications, a comparatively parsimonious empirical framework is adopted in the current analysis.

2.2. Variable Definition

All variables are defined as follows:

1. **ICT (Information and Communication Technology)**: Measured by the total telecommunications business volume (in 100 million yuan), which serves as a proxy for the development level of the ICT industry. Although ICT development is conceptually

multidimensional, this study adopts a monetary indicator due to data availability and consistency across provinces.

2. **GDPcap (Gross Domestic Product per capita)**: Per capita GDP of every province is one of the most important indicators of regional economic performance.

3. **TechInv (Technology Investment):** Based on technology market turnover in each province, which reflects the intensity of the innovation inputs in that region.

4. **PolStab (Policy Stability)**: The annual number of ICT-related policies multiplied by the standard deviation of the frequency of policy issuance between provinces.

5. **Reg (Policy Strength)**: The natural logarithm of the total number of ICT-related policies implemented per province.

These policy indicators are proxy measures based on policy frequency and are intended to capture policy activity rather than policy quality, which cannot be directly observed in the current dataset.

2.3. Data Sources

The economic and industrial statistics are aggregated using the official website of the National Bureau of Statistics of China, China Economic Net, and provincial statistical yearbooks. The policy data is taken out of PKULaw Local Laws and Regulations Database. The end result is a 713 province-year set of observations on 31 Chinese provinces between 2001 and 2023.

3. Empirical Results

3.1. Descriptive Statistics

As presented in Table 1, there are the descriptive statistics of all variables. The high standard deviations and large ranges of all variables imply that there is a high level of heterogeneity across provinces and with time. There are no outliers because all values lie in acceptable economic limits. The large gap between the maximum and minimum values of ICT development level and per capita GDP fully reflects the unbalanced development pattern of China's regional economy and ICT industry, which also verifies the necessity of studying the endogenous influencing factors from the provincial perspective.

Table 1

Descriptive Statistics of Variables (N=713)

Variable	Obs	Mean	Std. Dev.	Min	Max

ICT (100 million yuan)	713	886.81	1402.92	6.07	15025.30
GDPcap (yuan)	713	42018.72	33154.37	3000.00	200278.00
TechInv (100 million yuan)	713	398.01	967.69	0.00	8536.94
PolStab (items)	713	253.72	554.45	0.00	5748.30
Reg (items)	713	129.97	190.46	0.00	985.00

Note. All monetary variables are deflated to 2001 constant prices.

3.2. Correlation Analysis

Table 2 gives the Pearson correlation coefficients among the main variables. At a 1% significance level, all the explanatory variables were found to be positively related to lnICT, which provides preliminary support for the expected relationships proposed in this study. Correlation coefficients between independent variables are less than 0.8, which means that there is no severe multicollinearity issue.

Table 2

Pearson Correlation Coefficient Matrix

	lnICT	lnGDPcap	lnTechInv	PolStab	Reg
lnICT	1.000				
lnGDPcap	0.580***	1.000			
lnTechInv	0.619***	0.724***	1.000		
PolStab	0.223***	0.159***	0.130***	1.000	
Reg	0.401***	0.485***	0.427***	0.605***	1.000

Note. ***p < 0.001, **p < 0.01, *p < 0.05.

3.3. Model Selection Test

To identify the most suitable panel regression model, we perform three consecutive tests: F-test (fixed effects against pooled effects), Breusch-Pagan (BP) test (random effects against pooled effects), and Hausman test (fixed effects against random effects). It can be seen in Table 3 that all the tests are statistically significant at the 0.1% level, which means that the two-way fixed effects model is the best specification to use in this research.

Table 3

Model Selection Test Results

Test Type	Comparison	Test Statistic	Conclusion
F-test	FE vs. POOL	$F(30, 662) = 19.97$, $p < 0.001$	Select FE
BP Test	RE vs. POOL	$\chi2(1)=984.80$, $p < 0.001$	Select RE
Hausman Test	FE vs. RE	$\chi2(4)=37.50$, $p < 0.001$	Select FE

Note. FE = fixed effects; RE = random effects; POOL = pooled ordinary least squares (OLS); BP = Breusch–Pagan.

3.4. Baseline Regression Results

The results of random effects, time fixed effects, and two-way fixed effects regression are presented in Table 4. The overall significance test is passed by all the models ($p < 0.001$), which means that the model fit is good.

Table 4

Baseline Panel Regression Results

Variable	Random Effects	Time Fixed Effects	Two-way Fixed Effects
Intercept	-2.251*** (-3.96)	-3.156*** (-6.32)	-3.253*** (-6.63)
lnGDPcap	0.808*** (12.83)	0.849*** (15.46)	0.865*** (15.74)
lnTechInv	0.001 (0.02)	0.020* (2.13)	0.013 (1.45)
PolStab	0.000 (1.46)	0.000 (0.95)	0.000 (0.86)
Reg	-0.000 (-0.43)	0.000 (0.03)	-0.000 (-0.12)
Observations	713	713	713

R-squared	-	0.972	0.974
Model Test	$\chi2(4)$=590.86, p < 0.001	F(26, 640) = 799.91, p < 0.001	F(56, 610) = 821.34, p < 0.001

Note. T-statistics are in parentheses. ***p < 0.001, **p < 0.01, *p < 0.05.

The findings indicate that economic development level (lnGDPcap) has a positive and significant association with ICT development in all models, which supports the fact that it plays a crucial role as associated factor. The technological investment (lnTechInv) is meaningful only in the time fixed effects model, indicating clear dependence on the model. Policy stability (PolStab), policy strength (Reg), does not have a statistically significant influence on ICT development in the short term.

3.5. Supplementary Estimation Results

As an additional estimation exercise, this study further applies the Tobit model to examine whether the main empirical patterns remain broadly consistent under an alternative specification. Since the dependent variable is non-negative and exhibits substantial regional variation, the Tobit estimation is employed here primarily as a complementary sensitivity analysis rather than a definitive robustness test. Findings of the estimation results reported in Table 5 remain broadly consistent with the baseline panel regressions: the most important driver is the level of economic development, technological investment has a positive and statistically significant influence, and policy variables do not have a statistically significant effect.

Table 5

Supplementary Estimation Results (Tobit Model)

Variable	Coefficient	Std. Error	z	p	95% CI
Intercept	1.952***	0.539	3.62	<0.001	[0.895, 3.009]
lnGDPcap	0.308***	0.058	5.31	<0.001	[0.194, 0.422]
lnTechInv	0.224***	0.022	9.99	<0.001	[0.180, 0.268]
PolStab	0.000**	0.000	2.57	0.010	[0.000, 0.000]
Reg	0.000	0.000	1.24	0.216	[-0.000, 0.000]

Observations	713
Log Likelihood	-1023.45

Note. ***p < 0.001, **p < 0.01, *p < 0.05.

4. Discussion

4.1. The Fundamental Role of Economic Development

The results suggest that economic growth is a fundamental factor associated with the development of the ICT industry, potentially operating through both demand-side and supply-side mechanisms. In terms of demand, an increase in per capita income has altered consumer choices to move towards high-quality information products and services that encourage the consumption of telecommunications, internet access, and digital consumption (Wang and Li, 2024). Economically, the supply is driven by increased factor wages and increased market competition as companies are forced to use ICTs as a means of optimizing their production processes and enhancing overall factor productivity (Bloom et al., 2012). In the context of rising production costs, enterprises' demand for digital transformation is further amplified, and the scale expansion of the ICT industry is also driven by the continuous release of industrial digital demand.It pushes the industrial shift between human labor-intensive and capital-intensive industries and technology-intensive and information-intensive industries (Acemoglu and Restrepo, 2019).

4.2. Conditional Effect of Technological Investment

The heterogeneous nature of technological investment suggests that it does not necessarily contribute to the development of ICT automatically. It relies on the presence of complementary assets and an institutional context that should be favorable (Teece, 1986). Precisely, successful conversion of R&D investments into industrial development necessitates high quality human capital, an experienced innovation ecosystem, effective technology transfer systems, as well as sufficient financial assistance (Czarnitzki and Lopes-Bento, 2014). Pure R&D investment in regions where these conditions are not met can experience resource misallocation and innovation system failure, leading to decreasing marginal returns. These interpretations should be viewed as potential explanations rather than empirically verified mechanisms.

4.3. The Limited Short-Term Impact of Policies

The lack of significance of policy variables in the short term may suggest that factors such as policy quality and implementation could play a role, although these aspects are not directly tested in the current model (Aghion et al., 2015). The findings may imply that large-scale policy interventions alone are not necessarily sufficient to generate substantial short-term industrial outcomes, particularly when structural bottlenecks and regional institutional differences remain unresolved. Besides, policies tend to be associated with substantial time delays, as they manifest themselves in changing long-term institutional settings and market expectations, which cannot be measured in static contemporaneous regression models (Bloom et al., 2019). Therefore, the insignificant short-term effects should be interpreted with caution, as policy impacts may emerge over longer time horizons.

5. Conclusion and Policy Implications

This paper examines the key factors associated with ICT industry development in China using provincial panel data from 2001 to 2023. The major conclusions that can be made are:

1. The economic development level is found to be the most robust and consistently associated factor of the development of ICT with its positive influence on the basis of demand-side consumption upgrade as well as supply-side industrial transformation.

2. The investment in technology is conditionally promoting ICT development, and its efficacy depends on regional complementary assets and institutional environments.

3. The variables concerning policies have no general short-term effect on ICT development. The findings suggest that policy effectiveness may depend more on policy quality and implementation conditions than on policy quantity alone.

The results are of great policy significance. To begin with, it is important that policymakers focus on encouraging a well-balanced regional economy because this is the initial basis of the development of the ICT industry. In the context of the deep integration of the digital economy and the real economy, the policy implications derived from this research are more targeted for the high-quality development of the ICT industry, and can provide a practical reference for local governments to formulate differentiated industrial development strategies. Secondly, the technological investment must be supplemented by investments in complementary assets, including human capital and innovation infrastructure, to ensure the high effectiveness of these investments. Thirdly, rather than focusing on the amount of policy, the government should aim at enhancing the quality of policies, solving the underlying bottlenecks in industries, and creating institutional settings that are stable in the long run.

This paper can be further developed in future studies in two ways: (1) developing more advanced policy quality indicators based on text analysis techniques; (2) applying distributed lag models to measure the long-term dynamic impact of policies on ICT development.

Future research could further extend this analysis by incorporating dynamic models, lag structures, and interaction terms to capture more complex relationships.

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Author contributions

Conceptualization, Y.G.; methodology, Y.G.; formal analysis, Y.G.; investigation, Y.G.; writing—original draft preparation, Y.G.; writing—review and editing, Y.G. and A.M.; supervision, A.M. All authors have read and agreed to the published version of the manuscript.

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The authors declare that there is no conflict of interest.

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All authors have given their consent.

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