The Influence of Technology Advancement on Income Distribution Inequality

Chenge Luo

Department of Labor Relations, School of Labor Economics, Capital University of Business and Economics, Beijing, China

gege_13001228265@qq.com

Abstract. Technological progress has become a core driver of high-quality corporate development for China's pursuit of common prosperity, yet intra-firm income distribution inequality has become increasingly prominent. This paper empirically examines the impact of technological advancement on intra-firm income inequality using unbalanced panel data of 4,406 Chinese A-share listed companies from 2012 to 2024. We construct a two-way fixed effects model and conduct comprehensive robustness tests, endogeneity analysis (instrumental variable and DID methods) and heterogeneity research. The results show that technological advancement significantly exacerbates intra-firm income disparity, with a 0.0327-unit increase in the income distribution disparity index (IDD) per unit rise in technological advancement. Heterogeneity analysis indicates that the exacerbating effect is mainly concentrated in non-state-owned enterprises and high-growth enterprises.

Keywords: Technological Advancement, Income Distribution Inequality, A-Listed Companies

1 Introduction

Amid the in-depth integration of the global technological revolution and China's economic transformation, technological progress has emerged as a core driver of high-quality corporate development. It not only reshapes firms' production efficiency and competitive landscape but also exerts a profound impact on the equity of income distribution. With the widespread application of digitalization, intelligent manufacturing and other technologies among listed companies, the problem of income distribution inequality has become increasingly prominent. This is reflected both in the widening pay gap between senior executives and ordinary employees within enterprises and the growing income divergence between technology-leading firms and traditional ones—a phenomenon that has attracted extensive attention from academic circles and policymakers.

Theoretically, technological progress exerts a dual influence on income distribution. On the one hand, skill-biased technological progress raises the marginal product of high-skilled labor and gives rise to a skill premium. Meanwhile, management teams,

K. Othman et al. (eds.), *Proceedings of the 2026 5th International Conference on Mathematical Statistics and Economic Analysis (MSEA 2026)*, Advances in Economics, Business and Management Research 402,
https://doi.org/10.2991/978-94-6239-774-3_23

by virtue of their decision-making power in technological development and discretion over income distribution, gain an advantageous position, which may further widen internal income gaps. On the other hand, if the productivity gains and revenue growth brought by technological progress are transmitted to ordinary employees through a sound distribution mechanism, the imbalance in income distribution can be alleviated.

Current academic research on the impact of technological progress on income distribution inequality remains inadequate. In-depth analysis is still needed to explore the influence mechanisms and heterogeneous characteristics of technological progress on income distribution inequality among A-share listed companies. Clarifying the relationship between the two will not only enrich the empirical research in the fields of technological economics and income distribution theory but also provide academic support for enterprises to improve salary governance and for policymakers to optimize the distribution system, thus bearing important theoretical and practical significance.

2 Literature Review

Some scholars delved into income distribution and obtained some influential findings. Li (2024) supplements that economic globalization, as a crucial macro background, exacerbates income inequality through trade liberalization, capital circulation, and uneven technology diffusion. Based on this, Several scholars have conducted in-depth studies on the influencing factors, economic effects of income distribution inequality, and related changes in labor forms.[1] Clementi (2024) summarizes the global drivers of income inequality, providing cross-regional empirical references.[2] Zhou (2025) focuses on digital labor as a new form of labor. The study finds that while digital labor expands employment and promotes digital economic development, it faces dilemmas such as unfair value distribution, concealed capital exploitation, and alienation of labor relations. These issues further widen the income distribution gap, with the core crux lying in the monopolistic control of data and algorithms by platform capital.[3] Tian (2025) thinks that there is a significant inverted U-shaped nonlinear relationship between income distribution inequality and economic growth quality, with the inflection point corresponding to a Gini coefficient of 0.48. This relationship exhibits heterogeneity across eastern, central, and western regions, where the degree of marketization and economic development stage are key moderating variables.[4]

Gligovi (2024) points out that technological changes are the most important factor in economic growth.[5] Acemoglu (2022) & Restrepo (2023) categorize technological progress into four types—labor-augmenting, capital-augmenting, automation, and new task-creating—and clarify that different types exert distinct impacts on labor demand, factor shares and wages.[6] Acemoglu & Autor (2011) integrate skills, tasks and technology into a unified analytical framework, emphasizing that the matching between workers' skills and job tasks mediates the transmission of technological shocks.[7] In terms of empirical research, Autor, Dorn, Katz, Patterson & Van Reenen (2017, 2020) use U.S. data to illustrate that technological progress strengthens the market power of leading firms, thereby explaining the macro decline in labor share.[8] Autor & Salomons (2018) reveal that while technological progress may substitute labor at the industry level, it creates employment at the macro level through productivity-driven output expansion.

With the in-depth integration of technological revolution and economic development, technological progress has become a core factor affecting income distribution equity, attracting extensive academic attention. From a macro perspective, Bai & Wang (2025) argue that the direction of technological progress is key to explaining skill premium and regional wage gaps, noting that capital-biased technological progress widens gaps while labor-biased progress narrows them.[9] This study emphasizes that guiding technological progress toward a labor-biased direction and enhancing the capacity for independent innovation are effective pathways to narrow the income gap and achieve income equity. From a micro perspective, Liu & Yuan (2026) use data from online recruitment platforms and textual data from annual reports of A-share listed companies, find that AI narrows intra-firm income gaps by increasing average wages of ordinary employees more significantly than those of management.[10]

In conclusion, Scholars worldwide have made remarkable progress in studying the relationship between technological advancement and income distribution inequality. However, notable deficiencies and research gaps still exist in current studies, with the internal influence mechanisms remaining unclear: the research on the interaction between technological progress and other factors in shaping income inequality is insufficient; the heterogeneous research on how technological progress impacts income distribution inequality of A-share listed companies is still in its infancy; and there is a scarcity of studies on the dynamic evolutionary characteristics of emerging technologies' impacts on income inequality and the corresponding policy adjustment mechanisms, all of which call for further in-depth and targeted empirical research.

3 Data and Measurement

To ensure robust analysis, this study prioritizes rigorous data collection procedures. We extract secondary data from the China Stock Market & Accounting Research (CSMAR) database, a preeminent financial database in China. We implement data cleaning by eliminating firms with anomalous observations and applying 5% winsorization to mitigate extreme value influence. After preprocessing, our final sample comprises 37,217 firm-year observations spanning 2012-2024, encompassing 4,406 publicly listed companies.

4 Empirical Results

4.1 Regression model

After selecting variables and collecting data, this paper establishes an empirical regression model to analyze how technological advancement affects income distribution disparity. Since profit-maximizing enterprises adopt different strategies due to varying constraints and technologies, each has unique observable characteristics. Therefore, this study incorporates individual fixed effects to control for unobserved firm-specific heterogeneity and eliminate enterprise-specific influences. Given that both technological advancement and income distribution disparity have evolved substantially in recent years, we also include time fixed effects to account for temporal factors significantly affecting firm performance. This paper establishes a two-way fixed effect model to comprehensively analyze the impact of technological advancement on income distribution disparity while controlling for relevant variables. Finally, the specific regression model established is as follows:

$$IDD_{it} = \beta_0 + \beta_1 TECH_{it} + \gamma controls_{it} + m_i + \lambda_t + \mu_{it} \quad (1)$$

Where β_1 represents the influence coefficient of technological advancement on income distribution disparity, and controls are the controlled variables in the regression model, whose specific meaning and calculation method are illustrated in table 1.

Table 1. Table of variables.

Variables	Variable categories	Symbol for variables	Ways of calculating indices
Income distribution disparity	Explained Variable	IDD	The average income level of high rank employees / the average income level of the normal employees.
Technological advancement	Independent explanatory variable	TECH	The logarithm of the sum of patent number plus one
Size	Control Variables	SI	The logarithm of total assets
Return on assets		ROA	Net profit / total assets
Firm age		AGE	The age of the enterprise
Growth rate		GR	The growth rate of revenue: Changes in annual total revenue / Total revenue
Government subsidies		ZF	Amount of government subsidies from financial statements
Asset-liability ratio		ZZ	Total liabilities / Total assets
Executive Shareholding Ratio		SA	Executive shareholdings / Total shares
Largest shareholder holding ratio		TOP	The proportion of the largest shareholders in the company: Largest Shareholder's Holdings / Total Shares
Independent Director Ratio		DF	Number of independent directors / Total number of directors

Table 2. Statistical description table.

Variable	Observed Number	Mean	Standard Deviation	Minimum Value	Maximum Value
IDD	37217	5.9985	5.1275	1.5298	129.9892
TECH	37219	3.1360	1.6807	0	9.7057
SI	37219	22.2224	1.2820	18.8477	28.6437
ROA	37219	0.0385	0.6744	-1.1993	0.7585
AGE	37219	2.9144	0.3473	0.6931	4.2195
GR	37219	0.1985	6.2545	-0.9417	944.0996
ZF	37219	0.3898	0.1943	0.0079	1.2948
ZZ	37219	0.6181	0.5023	0.00001	12.1053
SA	37219	13.3637	0.6544	10.7213	16.7248
TOP	37219	0.3379	0.1499	0.0029	0.9183
DF	37219	0.0253	0.0262	0	0.5383

Table 2 provides detailed statistical descriptions of the variables employed in the regression analysis. After rigorous data cleaning and 5% winsorization processing to mitigate the impact of extreme values, there are no significant extreme outliers in all variables including the core explained variable, independent explanatory variable and control variables. Consequently, the distribution of all research variables falls within normal and reasonable ranges. These processed and screened data with good quality can be directly used to conduct the specific empirical analyses in the regression model.

4.2 Basic regression model

To explore the influence of technological advancement on income distribution inequality, this paper first conducts ordinary multivariate regression (Table 3). Results show that firms' income distribution inequality is significantly positively associated with technological advancement, indicating that technological progress tends to widen the intra-firm income gap between executives and ordinary employees. However, this baseline regression ignores unobserved firm-level heterogeneity. For more rigorous identification, this paper further implements estimations with firm fixed effects and two-way fixed effects. According to regression results (1), (2), and (3) in Table 3, technological advancement still imposes a significantly positive impact on income distribution inequality, proving that the baseline finding is stable and robust across different model settings.

Based on empirical analysis and variable characteristics, this paper selects the two-way fixed effects model as the optimal specification, and uses regression model (3) in Table 3 as the baseline estimation. Results show that the coefficient of technological advancement (TECH) is 0.0327, indicating that a one-unit increase in technological advancement is associated with a 0.0327-unit rise in income distribution inequality (IDD). We gradually add firm and year fixed effects. The coefficient of TECH remains significantly positive across all specifications, and we select the two-way fixed effects model (column 3) as our baseline. This indicates that technological advancement significantly exacerbates intra-firm income disparity.

Table 3. Regression Results Table.

IDD	IDD (1)	IDD (2)	IDD (3)
TECH	0.1055*** (0.0145)	0.1438*** (0.0203)	0.0326*** (0. 0154)
SI	-0.2392*** (0.2316)		-0.0892** (0.0377)
ROA	6.2471*** (0.3337)		1.2691*** (0.2339)
AGE	-1.1503*** (0.6059)		-0.0193 (0.2041)
GR	0.0046 (0.0032)		-0.0012 (0.0020)
ZF	1.9194*** (0.0032)		0.4821*** (0.1382)
ZZ	0.4549*** (0.0421)		-0.4376*** (0.5310)
SA	5.1347*** (0.0364)		6.3250*** (0.0392)
TOP	-0.9498*** (0.1413)		1.3281*** (0.2269)
DF	-32.3148*** (0.8838)		-10.3866*** (1.1941)
_cons	-54.4148*** (0.5189)	5.5488*** (0.0851)	-73.3426*** (0.9472)
Adj.R^2	0.4220	0.0301	0.4704
N	37217	37,217	29,757
Company control	N	Y	Y
Year control	N	Y	Y

Note: Standard errors in parentheses, *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

4.3 Robustness analysis

To test the robustness of the relationship between technological advancement and income distribution inequality, this paper adopts three approaches for robustness checks.

First, we exclude the 2024 observations due to the potential incomplete financial disclosure of listed firms. After re-regression, the results are consistent with the baseline findings. Second, we exclude central SOE samples. The salary systems of central SOEs are strictly regulated, which may distort the regression results. The estimated coefficient of technological advancement is still significantly positive after sample adjustment. Third, we add city-year interactive fixed effects to absorb unobservable time-varying city-level factors. The core coefficient remains significantly positive at the 1% level.

All robustness test results (Table 4) are consistent with the baseline regression, which verifies the stability of our core conclusion.

Table 4. Robust.Regression Results Table.

	(1)	(2)	(3)
tech1	0.0365**	0.0454***	0.0354**
	(0.0169)	(0.0167)	(0.0163)
si	-0.0591	-0.0838**	-0.1191***
	(0.0412)	(0.0406)	(0.0397)
roa	1.2891***	1.3330***	1.2808***
	(0.2521)	(0.2441)	(0.2436)
age	-0.1529	-0.1146	-0.0960
	(0.2259)	(0.2246)	(0.2163)
gr	0.0006	0.0012	0.0010
	(0.0021)	(0.0020)	(0.0020)
zf	0.5372***	0.5444***	0.3902***
	(0.1523)	(0.1484)	(0.1462)
zz	-0.4773***	-0.4667***	-0.4427***
	(0.0567)	(0.0568)	(0.0552)
sa	6.3851***	6.4511***	6.3948***
	(0.0427)	(0.0426)	(0.0417)
top	1.3833***	1.4783***	1.4348***
	(0.2450)	(0.2505)	(0.2427)
df	-11.3677***	-9.9328***	-10.1791***
	(1.3396)	(1.2625)	(1.2356)
_cons	-74.4225***	-74.7266***	-76.8373***
	(1.0393)	(1.0220)	(1.0693)
N	32839	33302	36180
R-squared	0.469	0.469	0.861
Individual control	Y	Y	Y
Year control	Y	Y	Y
City and year interaction control	N	N	Y

Note: Standard errors in parentheses, *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

4.4 Endogeneity analysis

To address the endogeneity issue, this paper adopts the Two-Stage Least Squares (2SLS) method for processing, so as to alleviate the potential endogeneity problems such as bidirectional causality and omitted variables between the core explanatory variable technological advancement and the intra-firm income distribution inequality. In the first stage of 2SLS, this paper takes the average value of technological advancement across regions as the instrumental variable (IV) for the core explanatory variable technological advancement (tech1). This instrumental variable only affects the intra-firm income distribution inequality through influencing the technological advancement level of enterprises in the region, which satisfies the relevance and exogeneity requirements of the instrumental variable. Meanwhile, all control variables in the previous baseline model, such as enterprise size, return on assets, enterprise age, operating revenue growth rate, as well as firm individual fixed effects and year fixed effects, are controlled in the model to fit the core explanatory variable technological advancement. In the second stage of 2SLS, this paper substitutes the fitted value of technological advancement obtained from the first-stage regression into the baseline model, and re-estimates the effect of technological advancement on the intra-firm income distribution inequality. The regression results show that after using the average value of regional technological advancement as the instrumental variable to alleviate the endogeneity problem, the coefficient of the core explanatory variable technological advancement is 0.2441, still significantly positive at the 1% statistical level, which is completely consistent with the direction and significance of the effect in the baseline regression, and the impact trend of technological advancement on the enterprise income gap has not changed. This indicates that the core research conclusion of this paper—technological advancement significantly exacerbates the intra-firm income distribution inequality—remains robust after accounting for the endogeneity issue (Table 5).

Table 5. Endogeneity Test Table

	(1) Tech1	(2)	(3)
techiv	0. 0184*** (0. 0051)	---	---
Tech1	---	0.2441*** (0.0681)	---
kk			0.1228*** (0 .0401)
Control variables	Y	Y	Y
C	-10.1209*** (0.3366)	17.6973*** (7.0306)	-73.2622*** (0.9436)
N	37217	37217	37217
R-squared	0.309	0.186	0.470
Individual control	Y	Y	Y
Year control	Y	Y	Y

To further alleviate potential endogeneity concerns such as omitted variable bias and reverse causality, this paper adopts the difference-in-differences (DID) method based on an exogenous policy shock. We use the 2019 national labor mobility reform as an exogenous policy shock, which provides a valid quasi-natural experiment.

We construct the following DID model:

$$IDD_{\text{it}} = \beta_0 + \beta_1 kk_{\text{it}} + \gamma controls_{\text{it}} + \mu_i + \lambda_t + \xi_{\text{it}} \quad (2)$$

Where $kk_{i,t} = mm_i \times dd_t$ is the core interaction term.$mm_i = 1$ if firm the technological advancement (tech1) of firm i is greater than or equal to the sample mean (3.13604), and 0 otherwise.$dd_t = 1$ for observations in and after 2019, and otherwise. We include firm fixed effects μ_i, year fixed effect λ_{t}, and all control variables used in the baseline regression.

The estimated coefficient of kk is 0.1228, still significantly positive at the 1% statistical level, which is still consistent with the baseline result. This indicates that after accounting for the exogenous policy shock, the positive effect of technological advancement on intra-firm income disparity remains robust, suggesting that our core conclusion is not driven by endogeneity issues.

4.5 Heterogeneity analysis

We conduct heterogeneity tests from two dimensions: enterprise ownership and growth rate, to explore the differential impacts of technological advancement (Table 6).

Table 6. Heterogeneity analysis

	(1)	(2)	(3)	(4)
tech1	-0.0291	0.0651***	0.0354**	-0.0058
	(0.0223)	(0.0203)	(0.0164)	(0.0439)
si	-0.1022*	-0.0934*	-0.2446***	0.1908*
	(0.0579)	(0.0483)	(0.0419)	(0.1012)
roa	-0.9389**	1.5342***	0.3238	0.4714
	(0.4690)	(0.2767)	(0.2603)	(0.7497)
age	0.4738*	-0.2353	-0.1857	0.5129
	(0.2839)	(0.2762)	(0.2213)	(0.5887)
gr	0.3218***	0.0011	0.4962***	-0.0001
	(0.0660)	(0.0021)	(0.0958)	(0.0026)
zf	0.3605*	0.4323**	0.4959***	-0.2216
	(0.2140)	(0.1777)	(0.1537)	(0.3780)
zz	-0.5273***	-0.3885***	-0.5001***	-0.4731***
	(0.0748)	(0.0710)	(0.0618)	(0.1249)
sa	5.4751***	6.7982***	5.9800***	7.3561***
	(0.0566)	(0.0520)	(0.0423)	(0.1100)
top	-0.0471	2.2209***	0.8485***	2.2832***
	(0.3016)	(0.3188)	(0.2383)	(0.6862)
df	-14.1256***	-9.9375***	-11.1675***	-9.4910***
	(2.4802)	(1.3883)	(1.3818)	(2.9057)
_cons	-63.4159***	-78.7193***	-64.9296***	-93.6211***
	(1.4747)	(1.2222)	(1.0587)	(2.5102)
N	11717	25500	26473	10744
R-squared	0.494	0.471	0.498	0.430
Individual control	Y	Y	Y	Y
Year control	Y	Y	Y	Y

Note: Standard errors in parentheses, *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

In terms of ownership heterogeneity, we divide the sample into SOEs and non-SOEs. The regression results show that technological advancement significantly widens the income gap of non-SOEs at the 5% level, while it has no significant impact on SOEs.

This is because SOEs are subject to strict salary regulation, and their wage setting is less affected by technological innovation; while non-SOEs are more market-oriented, and skill premiums caused by technology are more obvious.

In terms of growth rate heterogeneity, we divide the sample into high-growth and low-growth firms. Technological advancement has a stronger positive impact on the income gap of high-growth firms at the 1% level, but has no significant effect on low-growth firms. The reason is that high-growth firms have greater demand for high-skilled talents, thus amplifying the skill premium effect.

5 Conclusions

This paper empirically investigates the impact of technological advancement on intra-firm income distribution inequality using unbalanced panel data of 4,406 Chinese A-share listed companies from 2012 to 2024, and systematically conducts robustness tests, endogeneity analysis and heterogeneity research. The main conclusions are drawn as follows:

First, technological advancement significantly exacerbates the intra-firm income gap between executives and ordinary employees. The baseline regression results based on the two-way fixed effects model show that the coefficient of technological advancement (TECH) is 0.0327 and significantly positive at the 1% statistical level, meaning that a one-unit increase in technological advancement is associated with a 0.0327-unit rise in the intra-firm income disparity index (IDD).

Second, the impact of technological advancement on intra-firm income inequality exhibits significant ownership heterogeneity. The exacerbating effect of technological progress on income disparity is mainly concentrated in non-state-owned enterprises (non-SOEs), where the coefficient of technological advancement is significantly positive at the 5% statistical level. In contrast, technological advancement has no statistically significant impact on the internal income distribution of state-owned enterprises (SOEs). The underlying mechanism is that SOEs are subject to stricter administrative supervision and salary regulation due to their special institutional attributes and policy-oriented business objectives, making their wage-setting mechanisms less sensitive to market-based skill premiums brought by technological innovation. Non-SOEs, operating in a more market-oriented competitive environment, link income distribution more closely to employees' skill contributions and innovation performance, thus amplifying the skill premium effect and widening internal income gaps when adopting new technologies.

Third, the impact of technological advancement on intra-firm income inequality also shows significant growth rate heterogeneity. The exacerbating effect is primarily concentrated in high-growth enterprises, where the coefficient of technological advancement is significantly positive at the 1% statistical level and has a larger magnitude than the baseline regression coefficient. For low-growth enterprises with relatively stable operations and market positions, the impact of technological advancement on their internal income distribution is not statistically significant. This is because high-growth enterprises are in a stage of rapid business expansion and technological iteration, with stronger demand for high-skilled labor, and technological advancement further amplifies the income gap between high-skilled and low-skilled employees through the skill premium channel.

Based on the above conclusions, this paper puts forward the following targeted suggestions for enterprises and policymakers:

First, Enterprises should establish a fair technological dividend sharing mechanism and strengthen vocational training for ordinary employees. Second, Implement differentiated salary governance: SOEs should play a demonstrative role, while non-SOEs should standardize salary evaluation systems. Third, High-growth enterprises should balance technological innovation and income distribution equity by building multi-dimensional incentive systems.

References

1. Cai H J, Yang G J, Xing Y L. Does Artificial Intelligence Exert a Matthew Effect on Income Inequality? An Empirical Test Based on Microdata[J]. Journal of Shanxi University of Finance and Economics, 2025, 47(08):43-56. DOI:10.13781/j.cnki.1007-9556.2025.08.004.
2. Clementi F. Income Distribution, Inequality and Poverty: Evidence, Explanations and Policies[J]. Economies, 2024, 12(11): 276.
3. TIAN Z Y. The Nonlinear Impact of Income Distribution Inequality on the Quality of Economic Growth — An Empirical Study Based on Prefecture-Level City Panel Data[J]. Zhi Shi Jing Ji (The Knowledge Economy), 2025(32):134-137. DOI:10.15880/j.cnki.zsjj.2025.32.034.
4. ZHOU P. The Value, Dilemmas and Optimization Paths of Digital Labor[J]. Linyi Daxue Xuebao (Journal of Linyi University), 2025, 47(S1):31-41. DOI:10.13950/j.cnki.jlu.2025.S1.004.
5. Gligovi D .TECHNICAL PROGRESS AS A FACTOR OF ECONOMIC GROWTH [J]. Economy & Market Communication Review / Casopis za Ekonomiju i Trzisne Komunikacije, 2025, 15(1). DOI:10.7251/EMC2501195G.
6. Daron A, Pascual R. Tasks, Automation, and the Rise in U.S. Wage Inequality [J]. Econometrica, 2022, 90 (5): 1973-2016. DOI:10.3982/ECTA19815.
7. Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In D. Card & O. Ashenfelter (Eds.), Handbook of Labor Economics (Vol. 4, pp. 1043–1171). Elsevier.
8. Autor, D., Dorn, D., Katz, L.F., Patterson, C., & Van Reenen, J. (2017). Concentrating on the fall of the labor share. American Economic Review, 107(5), 180–185.
9. Bai Z, Wang X. Technological progress bias, wage income gap, and income equity [J]. Finance Research Letters, 2025, 81 107471-107471. DOI:10.1016/J.FRL.2025.107471.
10. Liu Dongsheng, Yuan Yuan. Artificial Intelligence, Skill Stripping, and Firm Income Gap[J]. Journal of Finance and Economics, 2026, 52(1): 123-137.