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The Impact and Mechanism of Technological Progress on Consumption Stratification: An Analysis from the Perspective of China’s Labor Market

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Abstract

Against the backdrop of the rapid development of new quality productive forces, technological progress profoundly reshaped income distribution patterns and consumption structures. On the basis of task-oriented model theory, this paper constructs an analytical chain of technological progress → employment polarization → consumption stratification using panel data from 30 Chinese provinces from 2008--2023. This study innovatively constructs a consumption entropy reduction index (CERI) to quantify the phenomenon of consumption stratification and identifies transmission mechanisms through an employment polarization index (EPI). The findings reveal that technological progress significantly exacerbates consumption stratification: each 1 percentage point increase in R&D investment intensity leads to an average increase of 0.018 units in the consumption entropy reduction index. Employment polarization plays a crucial mediating role, with technological progress leading to employment polarization through ‘skill-biased’ and ‘task-substitution’ mechanisms, which subsequently reshapes income distribution through wage–price mechanisms and ultimately transmits to the consumption domain, forming stratification. Further research indicates significant regional heterogeneity in the consumption stratification effects of technological progress, with more pronounced stratification effects in the eastern regions of China than in the central and western regions. This study is the first to construct a complete theoretical framework for how technological progress affects consumption stratification, providing important empirical evidence for coordinating technological innovation with common prosperity objectives.

Keywords

technological progress, consumption stratification, employment polarization, China’s labor market

1. Introduction

In the context of the rapid development of new quality productive forces, technological progress has become the dominant force driving economic growth, profoundly transforming people’s production and living patterns. Currently, emerging technology industries, represented by artificial intelligence, quantum computing, and biotechnology, have become key drivers propelling China’s economic transformation from ‘quantitative expansion’ to ‘quality improvement’ and achieving ‘high-quality development’. Data show that from 2019 to 2024, China’s core artificial intelligence industry scale grew from 71 billion yuan to 500 billion yuan, with an average annual growth rate exceeding 47% (National Bureau of Statistics, 2024). China has experienced the most profound structural economic transformation since its reform and opening up, which not only reshapes the allocation methods of production factors and industrial organizational forms but also profoundly influences the evolutionary trajectory of consumption structures by reconstructing supply–demand relationships in the labor market.

From the basic logic of economics, large-scale technological changes produce structural shocks to labor markets. This transmission process embodies the chain reaction effects of technological progress as an exogenous shock to economic systems. Research by Autor et al. based on task-oriented models indicates that technological change has biased effects on labor: intelligent technology has complementary effects with high cognitive-skilled labor, enhancing the marginal productivity of high-skilled workers, whereas automation technology directly replaces middle-skilled positions—particularly those involving routine, standardized operations—causing this group to face dual pressures of employment compression and income stagnation (Autor et al., 2003). Additionally, owing to their strong interpersonal interaction and nonstandardized tasks, low-skill service industries can maintain stable labor demand in the short term, creating a labor market 'safe haven' effect. Goos & Manning's empirical research on the UK labor market further confirmed that this employment 'polarization' phenomenon is a common challenge for developed economies (Goos and Manning, 2007).

Labor market differentiation transmits to the consumption sphere through wage–price mechanisms, which constitute the core pathway through which technological progress affects consumption structural changes. Technological transformation first alters the relative scarcity and bargaining power of workers with different skills, subsequently reshaping wage structures. Krueger's research revealed that computer use is significantly positively correlated with wage premiums, confirming the impact of technology on income distribution patterns (Krueger, 1993). When income distribution undergoes structural changes, different groups' consumption capacity and preferences significantly diverge: high-income groups benefit from technological dividends with rapidly growing disposable income, upgrading consumption structures toward quality-oriented, personalized developmental and enjoyment-type consumption; middle-income groups, affected by technological substitution, face employment uncertainty and income stagnation, exhibiting defensive consumption characteristics; and low-income groups, owing to limited and slowly growing income, mainly satisfy basic survival needs with limited space for consumption upgrading. This income-based consumption differentiation manifests not only at the aggregate level but also, more importantly, in structural quality differences, ultimately catalyzing consumption stratification phenomena.

However, existing research has obvious shortcomings. Theoretically, a complete analytical framework that organically connects technological progress, employment polarization, and consumption stratification is lacking, with most studies focusing on single-level impact mechanisms; methodologically, the quantification of consumption stratification phenomena relies mainly on traditional indicators, making it difficult to comprehensively characterize hierarchical differences in consumption structures across different groups; empirically, systematic research on the impact of technological progress on consumption structural changes in China's context, as well as sufficient verification of transmission mechanisms, is lacking.

On the basis of provincial panel data from 2008--2023, this study first classifies eight categories of consumption (food, clothing, housing) into basic, optional, and upgraded types according to consumption elasticity, constructing a consumption entropy reduction index (CERI) through information entropy principles to reflect consumption stratification and characterize hierarchical differences in consumption structures across different groups. To explore mechanisms in depth, the paper subsequently utilizes employment data from 19 industries across different provinces during the same period to construct an Employment Polarization Index (EPI) as a mediating variable, finding that technological progress indirectly drives consumption stratification by exacerbating employment polarization. Finally, with the implementation of the '13th Five-Year Plan' National Science and Technology Innovation Plan as a quasinatural experiment, a difference-in-differences model is constructed to identify the causal effects of technological innovation policies on consumption stratification; robustness checks are conducted through lag effect testing, and regional heterogeneity analysis is performed to verify the reliability of the results.

This study's innovations and research significance are reflected primarily in the following aspects. First, in terms of theoretical contribution, it pioneers the construction of a complete analytical chain of 'technological progress → employment polarization → consumption stratification', revealing the intrinsic mechanisms through which technological transformation affects consumption structural changes and deepening the understanding of the laws governing the effects of technological progress on economic and social structures. Second, with respect to research objects, it focuses on the dynamic evolution of consumption stratification, quantifying hierarchical differences across different groups in three consumption types through the consumption entropy reduction index, distinguishing it from existing research on ‘consumption upgrading’ through macro- or single-dimensional analysis, and providing a more detailed characterization of structural shocks from technological transformation to address livelihood needs. Third, in terms of practical value, empirical analysis based on China’s experience provides a reference for developing countries addressing technological transformation challenges and coordinating relationships between new quality productive force development and livelihood improvement, offering important guidance for formulating precise industrial, employment, and consumption policies.

2. Literature Review and Research Hypotheses

2.1 Direct Effects of Technological Progress on Consumption Stratification

Technological progress, as an important driving force for economic development, has long been an important topic in economics research regarding its impact on consumption structures. Early research focused mainly on the promotional effects of technological progress on overall consumption levels, with neoclassical growth theory represented by Solow, who argued that technological progress drives consumption growth by improving production efficiency and national income levels (Solow, 1956). However, this theoretical framework overemphasizes the inclusive effects of technological progress while ignoring heterogeneous impacts on different groups, making it difficult to explain increasingly prominent consumption differentiation phenomena in reality. As income distribution inequality problems become increasingly prominent, theoretical research gradually turns toward the distributional effects of technological progress. Zweimüller & Brunner analyzed the impact of income distribution on consumption structures relatively early from a product quality ladder model perspective, laying important foundations for subsequent research (Zweimüller and Brunner, 2005). These early theoretical studies’ main contributions lie in incorporating income distribution heterogeneity into consumption analysis frameworks but insufficiently revealing empirical mechanisms for how technological progress specifically affects consumption stratification.

In recent years, with the rapid development of digital transformation and artificial intelligence technology, academicians have achieved important breakthroughs in understanding the relationships between technological progress and consumption stratification. Arvai & Mann first systematically quantified digitalization’s impact on consumption inequality, finding that digitalization exacerbates consumption stratification not only through income effects but also through price effects—high-income households consume more digitally produced products, and these products have lower inflation rates, making consumption and welfare responses exhibit J-shaped rather than U-shaped distributions (Arvai and Mann, 2022). These findings overturn traditional theories’ understanding of the equalizing effects of technological progress, providing key insights for understanding the mechanisms of the stratification of the consumption of technological progress.

In empirical research, Richiardi et al. proposed the ‘conveyor belt hypothesis’ in their latest research on EU digital transformation, finding that digitalization significantly affects income inequality through employment status mediation during 2010--2019, with employed individuals having obvious advantages over unemployed individuals in responding to digitalization shocks (Richiardi et al., 2025). Anran Xiao et al., on the basis of cross-country research using data from 59 countries from 1995--2020, further confirmed that while technological innovation helps narrow communication and operational gaps, it significantly exacerbates income gaps in developed countries, and this differentiation necessarily transmits to consumption structural levels (Xiao et al., 2024).

On the basis of the above analysis, this paper proposes the first research hypothesis:

H1: Technological progress exacerbates the phenomenon of consumption stratification.

Technological progress, by reshaping income distribution patterns and consumption price structures, further widens differences in consumption capacity and preferences among different groups, thereby exacerbating consumption stratification phenomena.

2.2 Mechanisms of Technological Progress's Impact on Consumption Stratification

With respect to how technological progress affects consumption structures, the literature provides explanations of transmission mechanisms from a labor economics perspective. The development of task-oriented models provides an important theoretical foundation for understanding these transmission mechanisms. Autor et al., on the basis of task-oriented models, indicated that technological change has 'biased' effects on labor: intelligent technology has complementary effects with high cognitive-skill labor, whereas automation technology directly replaces routine operations in middle-skill positions (Autor et al., 2003). This theory lays a solid foundation for understanding the heterogeneous impacts of technological progress.

Employment polarization phenomena constitute the core transmission mechanism through which technological progress affects consumption stratification. Theoretical research has evolved from early skill-biased technological change to task-oriented analytical frameworks, with an increasingly sophisticated understanding of employment polarization. In subsequent research, Autor et al. systematically elaborated the concept of 'employment polarization', finding that employment growth mainly concentrates in high-skill, high-wage positions and low-skill, low-wage positions, whereas middle-skill position employment decreases (Autor et al., 2006). However, this classical theory is mainly based on U.S. experience, and its applicability to developing countries still requires verification.

Recent domestic and international research has provided a deeper understanding of the transmission mechanisms of technological progress, particularly new characteristics in the artificial intelligence era. Acemoglu & Restrepo reported that automation technology explains 50--70% of wage inequality changes in the U.S. since 1980, with this income differentiation scale far exceeding previous expectations (Acemoglu and Restrepo, 2022). Additionally, the impacts of technological progress are persistent—from 1987--2016, 16% of employment substitution effects were caused by automation, whereas only 10% of reconstruction effects were from new task creation. This asymmetry becomes key to understanding how technological progress continuously drives consumption stratification. Research in the context of China provides important insights into the experience of developing countries for understanding the transmission mechanisms of technological progress. Wang and Dong (2020), using manufacturing listed company data, reported that industrial robot applications produced significant substitution effects on enterprise labor demand, with these effects showing obvious differences across different skill levels. However, compared with rich research in developed countries, empirical analysis of complete transmission mechanisms for technological progress affecting consumption stratification in China's context remains insufficient, with existing research mostly focusing on the direct impacts of technological progress on labor markets and lacking systematic analysis of how this further transmits to consumption structural levels.

On the basis of theoretical analysis and empirical evidence, this paper identifies core transmission mechanisms through which technological progress affects consumption stratification. Specifically, technological progress first reshapes employment structures through 'skill-biased' and 'task-substitution' mechanisms, leading to labor market polarization; employment polarization further affects income distribution through wage–price mechanisms, with high-skill groups obtaining technological dividend premiums and middle-skill groups facing dual employment and income pressures, ultimately transmitting to the consumption sphere, forming a 'high-end consumption--middle-end consumption--basic consumption' stratification pattern.

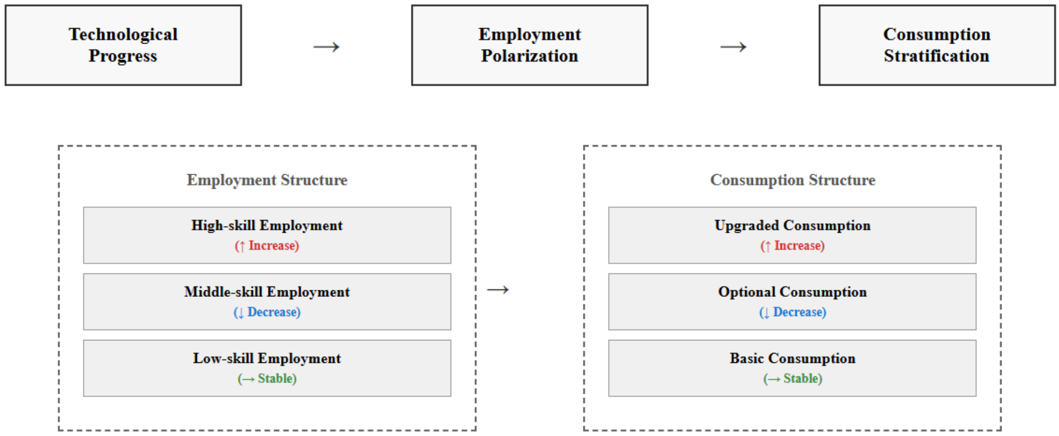
On the basis of the above research, this paper proposes the following research hypotheses:

H2: Technological progress exacerbates employment polarization phenomena.

H3: Technological progress indirectly affects consumption stratification through employment polarization.

As shown in Figure 1, technological progress first leads to employment polarization by changing employment structures and then affects income distribution patterns through wage differentiation, ultimately transmitting to the consumption sphere and exacerbating consumption stratification phenomena. Employment polarization plays an important mediating role in the transmission mechanisms through which technological progress affects consumption stratification.

Figure 1: Mechanism of the impact of technological progress on consumption stratification



3. Empirical Research Design

3.1 Data Sources and Sample Selection

The data used in this study come from multiple authoritative statistical departments and databases in China, with sample data sources divided into four categories: consumption expenditure data from the China Statistical Yearbook published by the National Bureau of Statistics and provincial statistical yearbooks; technological progress-related indicators from the China Science and Technology Statistical Yearbook, National Intellectual Property Office patent database, and Ministry of Science and Technology's National Science and Technology Funding Input Statistical Bulletin; employment data from the China Labor Statistical Yearbook by the Ministry of Human Resources and Social Security, China Population and Employment Statistical Yearbook by the National Bureau of Statistics, and industry employment statistics in the Wind database; and other control variable data from the China Statistical Yearbook by the National Bureau of Statistics, China Regional Financial Operation Report by the People's Bank of China, and China Education Statistical Yearbook by the Ministry of Education.

Considering data availability, completeness, and consistency, this study ultimately constructs a balanced panel dataset of 30 provinces, autonomous regions, and municipalities (excluding Tibet, Hong Kong, Macao, and Taiwan) from 2008--2023. The choice of 2008 as the starting year for research or analysis is mainly based on the following three considerations: first, China's economic structural adjustment accelerated after the 2008 financial crisis, with technology innovation-driven development strategies gradually established; second, the statistical calibres and classification standards for relevant statistical indicators remained relatively stable thereafter; third, this period covers complete policy cycles from the '12th Five-Year Plan' to the '14th Five-Year Plan', facilitating the identification of policy effects.

To ensure data quality, this study systematically cleaned the original data, removing obvious outliers and observations with excessive missing values. Linear interpolation was used to fill in a few missing data points; nominal variables were deflated via consumer price indices from each province, which were uniformly converted to real values with 2008 as the base period.

3.2 Variable Setting and Measurement Methods

Dependent Variable: Construction of the consumption entropy reduction index. On the basis of Engel's law and modern consumption theory, this study reclassifies eight categories of household consumption expenditures classified by the National Bureau of Statistics into three levels according to consumption elasticity characteristics. The specific classification basis is as follows: basic consumption (food and tobacco, clothing, housing) has lower income elasticity, belonging to survival-type consumption demand; upgraded consumption (education, culture and entertainment, medical care) has higher income elasticity, belonging to enjoyment-type consumption demand; and optional consumption (household goods and services, transportation and communication, and other consumption) has moderate income elasticity, belonging to development-type consumption demand. This classification method conforms to Maslow's hierarchy of needs theory and is consistent with consumption upgrading theory in consumption economics.

Drawing on the advantages of Shannon's information entropy theory in measuring distribution uniformity (Change, 1990), this study innovatively constructs a consumption entropy reduction index (CERI) to quantify consumption stratification phenomena. The specific construction steps are as follows:

Step 1: Calculate the proportions of the three types of consumption in each province:

$$p_{ij,t} = \frac{C_{ij,t}}{\sum_{j=1}^{3} C_{ij,t}}$$

where $C_{ij,t}$ represents the consumption expenditure of type j in province i in year t, and $p_{ij,t}$ is the corresponding consumption proportion.

Step 2: Calculate the Shannon information entropy of the consumption structure:

$$H_{i,t} = -\sum_{j=1}^{3} p_{ij,t}\, lnp_{ij,t}$$

The larger the information entropy is, the more uniform the consumption structure; the smaller the information entropy is, the more concentrated the consumption structure.

Step 3: Construct the consumption entropy reduction index:

$$CERI_{i,t} = H_{max} - H_{i,t}$$

where $H_{max} = ln3$ is the theoretical maximum entropy value (entropy value when three types of consumption are completely uniformly distributed). The CERI ranges from [0,ln3]. When CERI=0, equal proportions of three types of consumption (each accounting for 1/3), the most uniform consumption structure with no stratification phenomena, are indicated; when CERI approaches $ln3$, consumption is highly concentrated in one category with extremely severe stratification phenomena. The larger this index value is, the more the region's consumption structure deviates from a uniform distribution, and the more obvious the consumption stratification phenomenon. The advantages of this index are as follows: (1) it can simultaneously reflect the concentration and bias of consumption structures, and (2) it has good mathematical properties, facilitating econometric analysis.

Core Explanatory Variable: Measurement of Technological Progress Level. Technological progress, as the fundamental driving force for economic growth and structural transformation, requires accurate measurement for understanding technology–consumption relationships. Romer's (1990) endogenous growth model explicitly views R&D activities as sources of technological progress, with R&D investment directly determining the scale and intensity of technological innovation. Drawing on classical practices in endogenous growth theory and the technological innovation literature, this study uses R&D investment intensity as the core proxy variable for technological progress, which is specifically defined as follows:

$$Tech_{i,t} = \frac{R\&D_{i,t}}{GDP_{i,t}} \times 100\%$$

where $R\&D_{i,t}$ represents internal expenditures on research and experimental development in province i in year t and where $GDP_{i,t}$ is the corresponding regional GDP.

Control Variable Selection and Theoretical Basis. To control for other factors that might affect consumption structural changes and ensure accurate identification of technological progress impacts, this study selects the following control variables:

Economic development level (GDP): the natural logarithm of per capita regional GDP. According to Engel's law and Kuznets' inverted U-shaped hypothesis, income level is the fundamental factor determining consumption structure. As income levels rise, household consumption gradually shifts from basic to optional and upgraded types, while consumption capacity gaps between different income groups may widen, affecting the overall degree of consumption stratification.

Industrial structure (Tertiary) is the proportion of tertiary industry value added to regional GDP. Industrial structure upgrading usually accompanies changes in the employment structure and income distribution. Service industry development creates numerous high-skill employment positions while providing a rich supply for upgraded consumption, directly affecting the evolution of the consumption structure.

The human capital level (education) is the proportion of the population with higher education to the total population. Human capital is a key factor affecting technological absorption capacity and income acquisition ability. Highly educated populations usually have stronger technological adaptation capacity and higher income levels, with their consumption preferences and behaviors differing significantly from those of those with lower education levels.

Financial development level (Finance) is the sum of financial institution deposits and loans as a proportion of regional GDP. Financial development affects household consumption capacity and choices by providing consumer credit, investment and wealth management services. Developed financial markets facilitate consumption upgrading but may also exacerbate wealth gaps between different groups.

Degree of opening up (open) total import and export value as a proportion of regional GDP. Opening up leads to consumption concept updates and an increased variety of consumer goods, affecting consumption preferences and structures. Simultaneously, opening degrees also affect technological spillovers and industrial competition, indirectly acting on employment structures and the income distribution.

All continuous variables were subjected to descriptive statistical analysis and outlier treatment. For potential extreme values, trimming was performed at the 1% and 99% quantiles. Table 1 reports descriptive statistical results for the main variables.

Table 1: Descriptive Statistics

Variable	*Observations*	*Mean*	*Std. Dev.*	*Min*	*Max*
CERI	480	0.2054245	0.0525469	0.1027158	0.3655536
Tech	480	1.719557	1.131686	0.22	6.83
GDP	480	10.7558	0.5611	9.1796	12.2075
Tertiary	480	48.37569	9.4767	29.7	84.8
Education	480	14.38053	7.918493	3.063667	50.48593
Finance	480	3.348292	1.114638	1.453535	8.164073
Open	480	0.2819229	0.3028086	0.0076268	1.597324

From the distribution characteristics of the dependent variable consumption entropy reduction index (CERI), the sample period mean across provinces is 0.2054, and the standard deviation is 0.0526, with minimum and maximum values of 0.1027 and 0.3656, respectively. Considering that the theoretical maximum value of the CERI is ln 3 ≈ 1.099, the current values indicate that all regions in China exhibit varying degrees of consumption stratification phenomena, but the overall stratification degrees remain relatively moderate. Among these, the coefficient of variation of the CERI reaches 25.6%, reflecting significant differences in the degree of consumption stratification across different regions. The core explanatory variable, technological progress level (Tech), exhibits typical regional imbalanced distribution characteristics. The mean R&D investment intensity is 1.72%, reaching reasonable levels for developing countries but with a high standard deviation of 1.13 and a 6.61 percentage point difference between the maximum and minimum values. This large regional difference stems mainly from structural imbalances in innovation resource allocation between eastern coastal areas and central-western regions. From the perspective of distribution morphology, technological progress levels show an obvious right-skewed distribution, with a few innovation-leading regions having R&D investment intensities significantly higher than the national average, while most regions remain at relatively low levels.

3.2.1 Model Construction

To test the impact of technological progress on consumption stratification, this study constructs the following baseline regression model:

$$CERI_{it} = \alpha_0 + \alpha Tech_{it} + \sum_{k=1}^{5} \beta_k \, Controls_{kit} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where subscript i represents provinces (i = 1, 2...30), t represents years (j = 1, 2, 3); $CERI_{it}$ represents the consumption entropy reduction index; $Tech_{it}$ represents the technological progress level; $Controls_{kit}$ represents the kth control variable; μ_i represents province fixed effects, controlling for province-specific factors that do not vary with time; λ_t represents time fixed effects, controlling for common time trends affecting all provinces; and ε_{it} represents the random disturbance term satisfying classical assumptions. The core coefficient α is the main regression coefficient that this study focuses on, measuring the marginal impact of technological progress on consumption stratification. On the basis of theoretical analysis, $\alpha > 0$ expect that technological progress exacerbates consumption stratification phenomena.

4. Empirical Results and Analysis

4.1 Baseline Regression Testing

The baseline regression results are shown in Table 2. Under strict control of important variables, including economic development level, industrial structure, human capital, financial development, and degree of opening up, while incorporating province and time fixed effects, the estimated coefficient of technological progress (Tech) on the consumption entropy reduction index (CERI) is 0.018, passing the test at the 1% significance level. This result clearly verifies research hypothesis H1, namely, that technological progress significantly exacerbates consumption stratification phenomena. From the economic significance of the coefficients, each one percentage point increase in R&D investment intensity leads to an average increase of 0.018 units in the consumption entropy reduction index, which is equivalent to increasing the degree of consumption stratification by approximately 0.34 standard deviations.

To further examine the practical significance of the impacts of technological progress, a quantitative assessment can be conducted through the actual distribution of sample data. The interquartile range of technological progress levels during the sample period is approximately 1.8 percentage points. On the basis of this calculation, regions with higher technological innovation levels average 0.032 units higher consumption stratification degrees than those with lower levels do, accounting for 15.6% of the sample mean of the CERI. This difference manifests in reality as consumption structures in high-technology-level regions exhibiting more distinct hierarchical characteristics: high-income groups' expenditure proportions in upgraded consumption areas such as education, culture, entertainment, and healthcare significantly increase, whereas middle- and low-income groups' consumption expenditures remain concentrated mainly in basic consumption areas such as food, tobacco, alcohol, clothing, and housing, with relatively limited capacity and space for consumption upgrading.

Table 2: Baseline Regression Results

Variable	*CERI*
Tech	0.018***
	(2.879)
Constant	0.647**
	(2.261)
Adj_R²	0.3391
Observations	480
Control Variables	*Yes*
Time FE	*Yes*
Industry FE	*Yes*
Province FE	*Yes*

Note: t-statistics in parentheses; *, ** and * represent significance at the 10%, 5%, and 1% levels, respectively*

4.2 Robustness Checks

Lag Effect Testing. Consumer behavior, as an important component of individual economic decision-making, typically exhibits significant path dependence characteristics and adaptive adjustment processes. According to basic theories in consumption economics, consumers' behavioral patterns are not entirely immediate responses based on current income levels but are deeply influenced by multiple factors, including consumption habits, expectation formation, and psychological adaptation. Duesenberry's relative income hypothesis and Brown's consumption habit theory both emphasize persistent characteristics of consumption behavior, namely, that consumers tend to maintain established consumption patterns, with lagged responses to income changes (Duesenberry, 1949). More importantly, the impact of technological progress on consumption stratification often transmits through a series of intermediate channels before ultimately manifesting consumption structure changes, and this transmission process itself has obvious temporal dimensions. Technological progress first impacts labor markets, changing employment conditions and wage levels for different skill groups, after which income distribution pattern changes need to be further transmitted to consumption decision-making levels, whereas consumers' adaptation to income changes also requires certain adjustment periods. This dynamic adjustment process of consumption behavior means that the consumption stratification effects of technological progress may exhibit significant lags, with current consumption structures being influenced not only by current technological progress levels but also by the inertial effects of previous consumption patterns.

On the basis of this theoretical understanding, this study introduces lagged terms of dependent variables into the baseline regression model, constructing dynamic panel models to test whether consumption stratification phenomena exhibit self-reinforcing dynamic characteristics and whether technological progress impacts remain significant after controlling for consumption inertia. The lag effect model is specified as follows:

$$CERI_{it} = \alpha_0 + \alpha_1 Tech_{it} + \alpha_2 CERI_{it-1} + \sum_{k=1}^{5} \beta_k Controls_{kit} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

The lag effect test results in Table 3 show that the estimated coefficient of technological progress (Tech) is 0.015, remaining positive at the 5% significance level, indicating that the impact of technological progress on consumption stratification remains robust after controlling for consumption inertia. The lagged dependent variable coefficient ($CERI_{it-1}$) is 0.261, which is positive at the 10% significance level, indicating that consumption stratification phenomena have obvious self-continuation characteristics, with previous consumption structure differentiation partially continuing to the current period. This persistence mainly stems from the formation of consumption habits and the solidification of social stratification. On the one hand, differences in consumption patterns between different income groups, once formed, become reinforced through habit effects; on the other hand, consumption stratification often accompanies deep-level socioeconomic differentiation processes such as human capital accumulation and social network differences. The dynamic panel model estimation results verify the robustness of the baseline regression conclusions and reveal the temporal dimension characteristics of technological progress's impact on consumption stratification, namely, that technological transformation's reshaping of consumption structures is a gradual accumulative process requiring long-term, systematic policy combinations to address the consumption stratification challenges brought by technological progress.

Table 3: Lag Effect Testing

Variable	*CERI*
Tech	0.015**
	(2.455)
$CERI_{it-1}$	0.261*
	(1.848)
Constant	0.748***
	(3.351)
Adj_R2	0.0268
Observations	450
Control Variables	*Yes*
Time FE	*Yes*
Individual FE	*Yes*

Note: t-statistics in parentheses; *, ** and * represent significance at the 10%, 5%, and 1% levels, respectively*

DID Testing. *Model Design.* The '13th Five-Year Plan' National Science and Technology Innovation Plan (2016--2020), as China's first programmatic document elevating 'innovation-driven development' to a core national strategy, provides an ideal exogenous policy shock for this study. The plan explicitly proposes quantitative targets such as achieving total social R&D expenditure intensity above 2.5% by 2020 and doubling the number of high-tech enterprises compared with 2015. These indicators are directly related to this study's core explanatory variable (technological progress), and the policy formulation is centrally coordinated and unaffected by the local consumption structure and other micro factors, satisfying exogeneity requirements for quasinatural experiments. Therefore, this study employs difference-in-differences methods to identify the causal effects of technological progress on consumption stratification, with a specific design as follows:

First, the treatment and control group divisions are based on each province's R&D investment intensity in the year before policy implementation (2015). According to data from the China Science and Technology Statistical Yearbook 2016, the median R&D investment intensity across provinces in 2015 was 1.56%. Using this as the boundary, 30 provinces are divided into two groups: the treatment group (Treat = 1) includes 15 provinces with high R&D investment intensity, which have strong innovation foundations and faster technological progress after policy incentives; the control group (Treat = 0) includes 15 provinces with low R&D investment intensity and relatively weak innovation foundations, with smaller marginal policy impacts.

The difference-in-differences model is specified as follows:

$$CERI_{it} = \beta_0 + \beta_1 Treat_i \times Post_t + \beta_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

where $CERI_{it}$ is the dependent variable (consumption entropy reduction index); $Treat_i$ is the treatment group dummy variable (1 for the treatment group, 0 for the control group); $Post_t$ is the policy time dummy variable (1 for 2016--2023, 0 for 2008--2015); the core interaction term $Treat_i \times Post_t$ coefficient β_1 measures the net treatment effect of the policy; X_{it} is the control variable set (including 5 variables such as the economic development level and industrial structure); μ_i and λ_t are province and time fixed effects, respectively; and ε_{it} is the random disturbance term used to verify key model assumptions.

Table 4 presents descriptive statistical comparisons between the treatment and control groups in the difference-in-differences design. In terms of the intergroup differences in the core variables, the treatment group's technological progress level (Tech) mean is 2.463, which is significantly greater than that of the control group (0.976), with a group difference of 1.487 percentage points and a t statistic exceeding 8.0 ($p < 0.01$), indicating that the grouping design effectively captures fundamental differences in technological innovation capabilities across provinces.

Table 4: Descriptive Statistics

Variable	*Control Group*		*Treatment Group*	
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*
Treat	0	0	1	0
CERI	0.1954614	0.0511456	0.2153876	0.0521409
Tech	0.9759046	0.361719	2.463209	1.151208
GDP	10.48779	0.4485263	11.02374	0.5343139
Tertiary	45.8066	6.304983	50.94479	11.26867
Education	11.68346	4.40135	17.0776	9.575294
Finance	3.177751	0.745718	3.518832	1.369499
Open	0.1202098	0.0662478	0.443636	0.356174
Observations	240		240	

DID Regression Results Analysis. The difference-in-differences estimation results in Table 5 show that the net treatment effect between the treatment and control groups is 0.016, which is positive at the 5% significance level, indicating that implementation of the '13th Five-Year Plan' Science and Technology Innovation Plan indeed significantly exacerbated consumption stratification phenomena in high-technology-level regions. From a policy evaluation perspective, this result reveals unexpected distributional consequences of science and technology innovation policies while promoting technological progress. Policies effectively enhanced technological innovation capabilities in target regions through measures such as increasing R&D investment, cultivating high-tech enterprises, and improving innovation ecosystems but simultaneously exacerbated income differentiation between different skill groups, further manifesting as more obvious hierarchical characteristics at the consumption level.

Table 5: DID Regression Results

Variable	*CERI*
DID	0.016**
	(2.585)
Constant	0.688**
	(2.185)
Adj_R²	0.1932
N	480
Control Variables	*Yes*
Time FE	*Yes*
Individual FE	*Yes*

Note: t-statistics in parentheses; *, **, and * represent significance at the 10%, 5%, and 1% levels, respectively*

To verify the core identification assumptions of the difference-in-differences model, this study further constructs event study models to test parallel trend characteristics between the treatment and control groups before and after policy implementation. The event study model is specified as follows:

$$CERI_{it} = \alpha_0 + \sum_{k=-8}^{7} \alpha_k \, Treat_i \times Year_{t+k} + \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where $Year_{t+k}$ are time dummy variables relative to the policy implementation baseline year (2015), $k = -8$ to $k = -1$ correspond to 8 years to 1 year before policy implementation, k = 0 is the policy implementation year (2016), and k = 1 to k = 7 correspond to 1 year to 7 years after policy implementation. This model intuitively presents evolutionary trajectories of consumption stratification before and after policy shocks by estimating dynamic treatment effects at different time points.

The parallel trend test results shown in Table 6 indicate that in the 3 years before policy implementation (Before3) and 2 years before (Before2), the interaction term coefficients are -0.005 and -0.003, respectively, neither passing the statistical significance tests (t values of -0.530 and -0.474, respectively), indicating that the consumption entropy reduction indices (CERIs) of the treatment and control groups exhibited highly consistent evolutionary trends before policy intervention without systematic differences. This result strictly satisfies key identification requirements for difference-in-differences methods regarding parallel trends, effectively excluding endogeneity interference (such as selection bias caused by prepolicy differences).

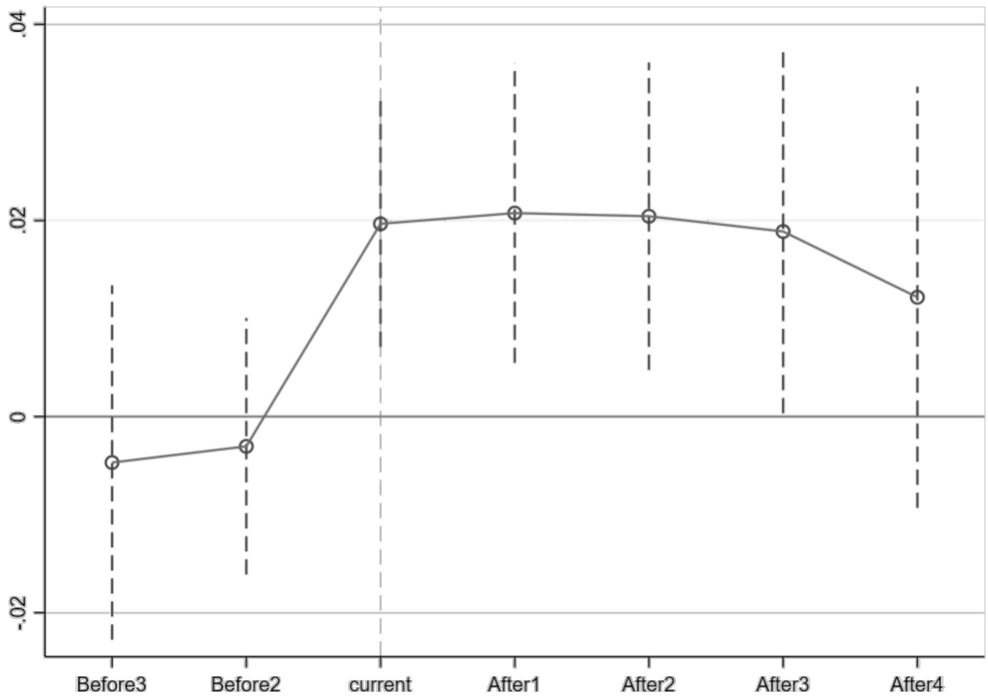
Table 6: Parallel Trend Testing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Before3	*Before2*	*Current*	*After1*	*After2*	*After3*	*After4*
	-0.005	-0.003	0.020***	0.021***	0.020**	0.019**	0.012
	(-0.530)	(-0.474)	(3.201)	(2.776)	(2.666)	(2.082)	(1.158)
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Individual FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Note: t-statistics in parentheses; *, ** and * represent significance at the 10%, 5%, and 1% levels, respectively*

Event study dynamic effect analysis further reveals temporal characteristics of policy impacts: the treatment effect coefficient in the policy implementation year (Current) is significantly positive (0.020***), indicating that the consumption stratification effects of technological innovation policy emerged during the policy initiation phase; the coefficients 1 year (After1) and 2 years after policy implementation (After2) are 0.021 and 0.020, respectively, maintaining statistical significance with stable effect intensity, reflecting the continuous release of policy shocks. This dynamic characteristic is consistent with technological progress transmission mechanism logic—technological innovation reshaping of labor markets is a gradual accumulative process, with path-dependent impacts on income distribution and consumption stratification that are difficult to reverse in the short term, thus exhibiting persistent effects.

Figure 2: Parallel Trend Testing Graph



4.3 Mechanism Testing: Employment Polarization Transmission Mechanism

To understand the intrinsic mechanisms through which technological progress affects consumption stratification in detail, this study tests the mediating role of employment polarization in this process. On the basis of task-oriented model theoretical frameworks, technological progress reshapes labor market structures by causing employment to concentrate toward both high-skill and low-skill positions, subsequently affecting income distribution and consumption structures.

Construction of Employment Polarization Index. Task-oriented models argue that different occupations involve different types of tasks, with technological progress having significantly different impacts on these tasks. *For middle-skill occupations involving routine cognitive and manual tasks, computers and automation technology have obvious substitution effects. For high-skill occupations involving nonroutine analytical and interactive tasks, technological progress often plays complementary roles. For low-skill occupations involving nonroutine manual tasks, owing to difficulty in standardizing task characteristics, short-term technological substitution possibilities are small.*

On the basis of this theoretical framework, this study constructs employment polarization indices via the following steps:

Step 1: Industry Classification and Skill Division

In accordance with the National Economic Industry Classification (GB/T 4754-2017), 19 major industries with relatively complete statistical data, including agriculture, forestry, animal husbandry and fishery, mining, manufacturing, electricity/heat/gas and water production and supply, construction, wholesale and retail, transportation/sports and entertainment, accommodation and catering, information transmission/software and information technology services, finance, real estate, leasing and business services, scientific research and technical services, water conservancy/environment and public facility management, residential services/repair and other services, education, health and social work, culture/sports and entertainment, public administration/social security and social organizations, are selected.

On the basis of average wage levels across industries, 19 industries are divided into three skill levels according to wage tertiles:

High-skill industries. Industries with average wages in the top 1/3 (mainly finance, information transmission and software, scientific research and technical services)

Middle-skill industries. Industries with average wages in the middle 1/3 (mainly manufacturing, construction, and transportation)

Low-skill industries. Industries with average wages in the bottom 1/3 (mainly including agriculture/forestry/animal husbandry/fishery, accommodation and catering, and residential services)

Step 2: Employment Polarization Index Calculation

$$EPI_{i,t} = (High_{i,t} + Low_{i,t}) - 2Mid_{i,t} - ((High_0 + Low_0) - 2Mid_0)$$

where $High_{i,t}$, $Low_{i,t}$, and $Mid_{i,t}$ represent employment proportions in high-skill, middle-skill, and low-skill industries, respectively, for province i in year t, with the subscript 0 representing base period levels.

This index measures employment polarization degrees by comparing differences between current and base period employment structures. When the EPI > 0, compared with the base period, current employment concentrates more toward both high-skill and low-skill positions, with employment polarization phenomena present; larger EPI values indicate more severe degrees of polarization. When the EPI < 0, employment concentrates more in middle-skill positions with alleviated polarization phenomena. When EPI = 0, the employment distribution is identical to that in the base period.

Model Construction. To verify the mediating role of employment polarization in the effect of technological progress on consumption stratification processes, this study employs the three-step method proposed by Baron & Kenny for testing, setting up mediation effect testing models (5) and (6) on the basis of baseline Model (1).

$$EPI_{it} = b_0 + b \cdot Tech_{it} + \sum_{k=1}^{5} \psi_k Controls_{kit} + \mu_i + \lambda_t + \varepsilon_{2it} \tag{5}$$

$$\mathrm{C}ERI_{it} = c_0 + c \cdot Tech_{it} + c' \cdot EPI_{it} + \sum_{k=1}^{5} \theta_k Controls_{kit} + \mu_i + \lambda_t + \varepsilon_{3it} \tag{6}$$

According to mediation effect theory, if coefficients a, b, and c’ are all significant and |c’| < |a|, then mediation effects exist. The mediation effect size is b × c’, accounting for (b × c’)/a proportion of total effects.

Mediation Effect Testing Results. The results of the mediation effect tests in Table 7 provide key evidence for understanding the transmission mechanisms through which technological progress affects consumption stratification. First-step testing reveals that the impact coefficient of technological progress (Tech) on the employment polarization index (EPI) is 0.048, which is positive at the 5% significance level, indicating that each one percentage point increase in R&D investment intensity leads to an average increase of 0.048 units in degrees of employment polarization. This result supports research hypothesis H2, namely, that technological progress indeed exacerbates employment polarization phenomena. From a theoretical perspective, technological progress mainly substitutes middle-skill occupations involving routine cognitive and manual tasks while having relatively limited impacts on high-skill work requiring complex problem-solving abilities and low-skill service work that is difficult to program, thereby causing employment structure polarization toward both ends.

While simultaneously incorporating technological progress and employment polarization, second-step testing reveals that the estimated coefficient of the consumption entropy reduction index (CERI) for employment polarization (EPI) is 0.041, passing tests at the 1% significance level and confirming that employment polarization is indeed an important mechanism driving consumption stratification. Specifically, each one-unit increase in the employment polarization index leads to an average increase of 0.041 units in the degree of consumption stratification. Simultaneously, the direct effect coefficient of technological progress decreases from the baseline regression coefficient of 0.018 to 0.013, a 27.8% reduction with obviously weakened impact intensity. This coefficient change pattern indicates the existence of a mediating effect, verifying research hypothesis H3, namely, that technological progress indirectly affects consumption stratification through employment polarization.

Table 7: Mediation effect testing

Variable	*EPI*	*CERI*
EPI		0.041***
		(2.778)
Tech	0.048**	0.013*
	(2.062)	(1.975)
Constant	-3.714**	0.799**
	(-2.632)	(2.677)
Adj_R2	0.1356	0.2135
Observations	480	480
Control Variables	*Yes*	
Time FE	*Yes*	
Industry FE	*Yes*	
Province FE	*Yes*	

Note: t-statistics in parentheses; *, **, and * represent significance at the 10%, 5%, and 1% levels, respectively*

Technological progress first reshapes labor market demand structures through dual mechanisms of 'skill bias' and 'task substitution', increasing relative demand for high-skilled labor and reducing demand for middle-skilled labor while having relatively neutral impacts on low-skilled labor, forming employment polarization patterns toward both ends. Employment polarization subsequently affects income distribution through wage–price mechanisms: high-skill groups benefit from technological dividends and scarcity premiums with rapidly rising income levels; middle-skill groups face technological substitution threats with contracting employment opportunities and stagnant income growth; and low-skill groups, while having relatively stable employment, generally have low income levels. Changes in this income distribution pattern ultimately map to consumption spheres, manifesting as differences in consumption capacity and preferences among different income groups: high-income groups possess stronger consumption capacity and tend toward quality-oriented, personalized upgraded consumption; middle- and low-income groups have limited consumption capacity, mainly satisfying basic survival needs with relatively insufficient space and motivation for consumption upgrading, thus forming obvious consumption stratification phenomena.

4.4 Regional Heterogeneity Analysis

Given the significant spatial differentiation characteristics of China's economic development, the impact of technological progress on consumption stratification may exhibit regional differences. To explore this spatial heterogeneity in depth, this study constructs grouped regression models:

$$CERI_{it} = \alpha_0^k + \alpha_1^k Tech_{it} + \sum_{j=1}^{5} \beta_j^k \, Controls_{jit} + \mu_i^k + \lambda_t^k + \varepsilon_{it}^k \tag{7}$$

where the superscript k represents different regions ($k = East, Central, West$), α_1^k represents heterogeneous coefficients of the impact of technological progress on consumption stratification across regions).

The regression results shown in Table 8 indicate that the impact coefficients of technological progress on consumption stratification exhibit completely opposite signs across different regions. The coefficient for the eastern region is 0.028 and significant at the 1% level, whereas the coefficient for the central region is -0.027 and significantly negative at the 10% level; the coefficient for the western region is 0.006 but statistically insignificant.

Table 8: Heterogeneity Analysis

Variable	*Eastern*	*Central*	*Western*
	CERI	*CERI*	*CERI*
Tech	0.028**	-0.027*	0.006
	(3.049)	(-2.088)	(0.536)
Constant	0.055	-0.328	1.152**
	(0.085)	(-0.666)	(3.034)
Adj_R²	0.2130	0.2723	0.1718
Observations	176	128	176
Control Variables	*Yes*	*Yes*	*Yes*
Time FE	*Yes*	*Yes*	*Yes*
Individual FE	*Yes*	*Yes*	*Yes*

Note: t-statistics in parentheses; *, ** and * represent significance at the 10%, 5%, and 1% levels, respectively*

Regional heterogeneity analysis of the impact of technological progress on consumption stratification reveals differentiated mechanisms of technological transformation at different economic development stages. The regression results reveal that the eastern region's technological progress coefficient is 0.028 and significantly positive at the 1% level, the central region's coefficient is -0.027 and significantly negative at the 10% level, and the western region's coefficient is 0.006 but statistically insignificant, reflecting the complexity and conditional dependence of the impact of technological progress on changes in the consumption structure.

The eastern region, as an economically developed area with highly advanced industrial structures and high technology intensity, shows that technological progress operates mainly through 'skill-biased' mechanisms. New technology applications accompany labor market reconstruction, with high-skilled workers obtaining significant income premiums due to complementarity with advanced technologies, whereas middle- and low-skilled workers face technological substitution shocks, leading to differentiated income distribution patterns that subsequently transmit to consumption structural levels through consumption capacity differences, manifesting as exacerbated consumption stratification phenomena.

The negative effects presented in central regions reflect the 'equalizing' role of technological progress. As important regions for undertaking industrial transfer, technological progress in central regions manifests more as gradual technological improvements and efficiency enhancements. Technological progress benefits different income groups through improving overall production efficiency and reducing production costs, particularly for middle- and low-income groups, where technological progress-induced cost reductions and increased employment opportunities can significantly improve consumption capacity, thereby alleviating consumption structure differentiation trends.

The statistically insignificant coefficient in the western region reflects the reality of relatively lagged technological development levels in these areas. Under conditions of weak technological foundations, the reshaping effects of technological progress on economic and social structures have not yet fully manifested, with impact mechanisms on consumption stratification still in the gestation stages. As regional coordinated development strategies are implemented, the technological innovation capabilities of western China will gradually improve, and the impact of technological progress on consumption structures will become more significant.

From an impact mechanism perspective, the comprehensive effects of technological diffusion speed, industrial structure characteristics, and degree of labor market segmentation provide an in-depth analysis. In regions with active technological innovation and high industrial structure advancement, technological progress often accompanies more intense creative destruction processes, with new technologies rapidly substituting traditional production methods, leading to obvious 'advantage concentration' situations in labor markets. Conversely, in regions dominated by traditional industries with relatively slow technological diffusion, technological progress manifests more as gradual improvements with relatively mild impacts on existing employment structures, potentially benefiting broader consumer groups through scale economy effects and cost reduction mechanisms. Therefore, for regions at different development stages, the social and economic consequences of technological innovation policies may be completely different, requiring differentiated policy designs to maximize the positive effects of technological progress while controlling for negative impacts.

5. Conclusions

Against the backdrop of the rapid development of new quality productive forces, technological progress, as the core driving force for high-quality economic development, is profoundly reshaping China's economic and social landscape. On the basis of provincial panel data from 2008--2023, this study constructs consumption entropy reduction indices and employment polarization indices to systematically examine the impact of technological progress on consumption stratification and transmission mechanisms. Research findings show that technological progress significantly exacerbates consumption stratification, with this effect being realized mainly through employment polarization. Specifically, technological progress first reshapes employment structures through 'skill bias' and 'task substitution' mechanisms, with high-skill labor experiencing increased demand due to complementarity with intelligent technology, low-skill service industries maintaining employment stability due to nonstandardized tasks, and middle-skill positions facing significant automated substitution shocks, forming polarized employment patterns concentrated toward both ends. Through wage–price mechanisms affecting income distribution, high-skill groups subsequently obtain technological dividend premiums, whereas middle-skill groups face dual employment and income pressures, ultimately transmitting to consumption spheres and forming 'high-end consumption–middle-end consumption–basic consumption' stratification patterns.

Further regional heterogeneity analysis reveals the complexity and conditional dependence of the impact of technological progress on consumption stratification. Eastern regions rely on 'skill bias' mechanisms to exacerbate stratification, central regions produce 'equalizing' effects through gradual technological improvements to alleviate consumption differentiation, and western regions have insignificant impacts due to weak technological foundations. These differences reflect China's economic spatial imbalance characteristics, providing the basis for differentiated regional policies. Simultaneously, difference-in-differences analysis using the implementation of the '13th Five-Year Plan' National Science and Technology Innovation Plan as a quasinatural experiment confirms that technological innovation policies indeed produce unexpected distributional consequences while promoting technological progress, with policy effects emerging in implementation years and continuously releasing, reflecting path dependence and the persistence characteristics of technological progress transmission mechanisms.

In the future, academia still has broad development space, and important theoretical propositions await in-depth exploration in the fields of technological transformation and consumption stratification research. With the deep integration of digital and real economies, the reshaping effects of digital technology on traditional consumption patterns have become increasingly prominent, with the impacts and reconstruction effects of emerging consumption forms such as digital consumption, the platform economy, and the sharing economy on traditional consumption stratification patterns becoming academic focuses. As technology progresses, applications of big data, machine learning, and other tools provide new possibilities for characterizing consumption behavior dynamics. From micro foundations, the regulatory roles of individual cognitive abilities, risk preferences, and other psychosocial factors in the transmission of technological shock to consumption behaviors, as well as the long-term impacts of intergenerational adaptive differences on consumption pattern evolution, still require deep analysis. More importantly, in the new journey of Chinese-style modernization construction, how to better serve common prosperity goals through institutional innovation and policy coordination, enabling technological progress to achieve the inclusive sharing of technological dividends, will become the most urgent practical issue in this research field.

References

Acemoglu, D. and Restrepo, P., (2022). Tasks, automation, and the rise in US wage inequality. *Econometrica,* vol. 90**,** no. 5, pp. 1973-2016.

Arvai, K. and Mann, K., (2022). *Consumption inequality in the digital age* [Online]. SUERF Policy Brief No. 526. Available: https://www.suerf.org/docx/f_e822eb93c2ab172e4c89bdba93857d60_61711_suerf.pdf.

Autor, D. H., Katz, L. F. and Kearney, M. S., (2006). The polarization of the US labor market. *American Economic Review,* vol. 96**,** no. 2, pp. 189-194.

Autor, D. H., Levy, F. and Murnane, R. J., (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics,* vol. 118**,** no. 4, pp. 1279-1333.

Change, E. T., (1990). Endogenous technological change. *Journal of Political Economy,* vol. 98**,** no. 5, pp. S71-S102.

Duesenberry, J. S., (1949). Income, saving, and the theory of consumer behavior. *Review of Economics & Statistics,* vol. 33**,** no. 3, p. 111.

Goos, M. and Manning, A., (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *The review of economics and statistics,* vol. 89**,** no. 1, pp. 118-133.

Krueger, A. B., (1993). How computers have changed the wage structure: evidence from microdata, 1984–1989. *The Quarterly Journal of Economics,* vol. 108**,** no. 1, pp. 33-60.

National Bureau of Statistics, (2024). *Economic Structure Continuously Optimized, Development Coordination Significantly Enhanced—The Eighth in a Series of Reports on the Achievements of China's Economic and Social Development Over the Past 75 Years* [Online]. Available: https://www.stats.gov.cn/sj/sjjd/202409/t20240912_1956415.html [Accessed December 12, 2025].

Richiardi, M. G., Westhoff, L., Astarita, C., Ernst, E., Fenwick, C., Khabirpour, N. and Pelizzari, L., (2025). The impact of a decade of digital transformation on employment, wages, and inequality in the EU: a "conveyor belt" hypothesis. *Socio-Economic Review*, p. mwaf011.

Solow, R. M., (1956). A contribution to the theory of economic growth. *The quarterly journal of economics,* vol. 70**,** no. 1, pp. 65-94.

Wang, Y. and Dong, W., (2020). How does the rise of robots affect China's labor market? Evidence from manufacturing listed companies. *Economic Research Journal,* vol. 55**,** no. 10, pp. 159-175.

Xiao, A., Xu, Z., Skare, M., Qin, Y. and Wang, X., (2024). Bridging the digital divide: the impact of technological innovation on income inequality and human interactions. *Humanities and Social Sciences Communications,* vol. 11**,** no. 1, p. 815.

Zweimüller, J. and Brunner, J. K., (2005). Innovation and growth with rich and poor consumers. *Metroeconomica,* vol. 56**,** no. 2, pp. 233-262.

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